

Dakota State University Beadle Scholar

Masters Theses & Doctoral Dissertations

Fall 8-1-2017

Users' Continuance Participation in Online Health Communities: Short-term vs. Long-term

Yanyan Shang
Dakota State University

Follow this and additional works at: <https://scholar.dsu.edu/theses>

Recommended Citation

Shang, Yanyan, "Users' Continuance Participation in Online Health Communities: Short-term vs. Long-term" (2017). *Masters Theses & Doctoral Dissertations*. 310.
<https://scholar.dsu.edu/theses/310>

This Dissertation is brought to you for free and open access by Beadle Scholar. It has been accepted for inclusion in Masters Theses & Doctoral Dissertations by an authorized administrator of Beadle Scholar. For more information, please contact repository@dsu.edu.



**< USERS' CONTINUANCE PARTICIPATION IN
ONLINE HEALTH COMMUNITIES: SHORT-TERM VS.
LONG-TERM >**

A dissertation submitted to Dakota State University in partial fulfillment of the requirements
for the degree of

Doctor of Science

in

Information Systems

<August, 2017>

By

<Yanyan Shang>

Dissertation Committee:

<Jun Liu>

<Insu Park>

<Dorine Bennett>



DISSERTATION APPROVAL FORM

This dissertation is approved as a credible and independent investigation by a candidate for the Doctor of Science in Information Systems degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this dissertation does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department or university.

Student Name: Yanyan Shang

Dissertation Title: Users' Continuance Participation in online health Communities:

Short-term vs. Long-term

Dissertation Chair/Co-Chair:

Punhui

Date:

8/8/2017

Dissertation Chair/Co-Chair:

Date:

Committee member:

Insu Park

Date:

08/08/2017

Committee member:

Donna Bennett

Date:

8/8/17

Committee member:

Date:

Committee member:

Date:

ACKNOWLEDGMENT

I would never have been able to finish my dissertation without the guidance of my committee members and support from my family.

I would like to express my deepest gratitude to my advisor and dissertation Chair, Dr. Jun Liu, for his excellent guidance, patience, and support to my research and dissertation. I would also like to thank my dissertation committee members, Dr. Insu Park and Dr. Dorine Bennett, for guiding my research and helping me to develop my background in information systems.

Most importantly, I would like to thank my parents for their love and support throughout my life. Thank them both for giving me the strength to chase my dreams.

ABSTRACT

As one of the most promising health-related social media services, the online health communities (OHCs) have been developed and exponentially increased in the past decade. Patients can benefit from the participation of OHC discussions by obtaining information and knowledge, receiving support and releasing mental stress. The purpose of this study is to identify factors that affect the users' continuance participation and to examine their different influences in the short-term and long-term stages survival and activeness in the OHCs. We conducted two separate studies to investigate users' continuance participation in terms of survival time and activeness.

Our research makes two major contributions. First, we identify the factors that determine users' short-term vs. long-term survival. Specifically, we propose a new construct, the initial goal, to social support theory. Results show that the information seeking goal and the emotional seeking goal will drive users into different stages of their membership life cycle. Additionally, the appropriate self-interaction discussion pattern has a positive impact on users' long-term survival. Second, we identify the factors that lead to users' short-term and long-term activeness. Our study compares the users' participation behavior during the different stages and predicts their post-stage activeness based on expectation-confirmation theory. Our findings show that the social support and recognition in the initial stage play important roles in the short-term activeness, whereas the social attachment in the short-term stage increases its impact on the long-term activeness.

DECLARATION

I hereby certify that this dissertation constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the dissertation describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,



Yanyan Shang

<Student name>

TABLE OF CONTENTS

DISSERTATION APPROVAL FORM.....	II
ACKNOWLEDGMENT	III
ABSTRACT	IV
DECLARATION	V
TABLE OF CONTENTS	VI
LIST OF TABLES.....	VIII
LIST OF FIGURES.....	IX
INTRODUCTION	1
BACKGROUND OF THE PROBLEM	1
STATEMENT OF THE PROBLEM	3
OBJECTIVES OF THE PROJECT	4
LITERATURE REVIEW	6
STUDY DESIGN	11
STUDY I: SHORT-TERM VS. LONG-TERM SURVIVAL.....	14
THEORY BUILDING AND HYPOTHESIS DEVELOPMENT.....	14
<i>Initial stage participation clue for short-term vs. long-term survival.....</i>	<i>14</i>
RESEARCH METHODOLOGY	27
<i>Model Measurements</i>	<i>27</i>
<i>Data collection.....</i>	<i>29</i>
<i>Model results.....</i>	<i>34</i>
FINDINGS AND DISCUSSION	38
THE PREDICTION OF USERS SHORT-TERM VS. LONG-TERM SURVIVAL.....	45
STUDY II: SHORT-TERM VS. LONG-TERM ACTIVENESS.....	48
THEORY BUILDING AND HYPOTHESIS DEVELOPMENT.....	48
<i>The current stage benefits of participation clue to post-stage activeness</i>	<i>49</i>
<i>The current stage participating characteristics clue to post-stage activeness.....</i>	<i>58</i>
RESEARCH METHODOLOGY	61
<i>Model Measurements</i>	<i>61</i>

<i>Data collection</i>	63
<i>Model results</i>	65
FINDINGS AND DISCUSSION	68
CONCLUSION	76
CONCLUSION	76
LIMITATIONS	77
REFERENCE	78
APPENDIX	85
LOGISTIC REGRESSION RESULTS (STUDY I).....	85
REGRESSION RESULTS (STUDY II).....	86
<i>Model 1: Dependent variable: Short-term stage activeness</i>	86
<i>Model 2: Dependent variable: Long-term stage activeness</i>	86

LIST OF TABLES

Table 1 Studies on Users' Participation in Online Communities.	8
Table 2 Studies on Online Health Community	9
Table 3 Description of Membership Life Cycle Stages	12
Tabel 4 Constructs and Measurements	27
Table 5 The Users' Stay Length.....	32
Table 6 The Users' Statistics by Membership Life Cycle Stages	34
Table 7 Descriptive Statistics for Variables.....	36
Table 8 Results of ANOVA Analysis	37
Table 9 Results of Correlation Analysis	38
Table 10 Summary of Findings of Study I.....	44
Table 11 Logistic Regression Output for Study I	45
Table 12 Member Benefits of Participation	50
Table 13 Model Measurements and Variable Descriptions	62
Table 14 The Descriptive Statistics of Users' Activeness	64
Table 15 Descriptive Statistics of Variables for Short-term Activeness.....	65
Table 16 Regression Output for Model 1.....	66
Table 17 Descriptive Statistics of Variables for Long-term Activeness.....	67
Table 18 Regression Output for Model 2.....	68
Table 19 Comparison of Regression Output for Model 1 and Model 2	68
Table 20 Summary of Findings of Study II	74

LIST OF FIGURES

Figure 1 Research Model for Study I.....	27
Figure 2 The Data Processing	31
Figure 3 Users' Stay Length and Frequency Distribution	33
Figure 4 The Users' Statistics by Membership Life Cycle (Initial/Short-term/Long-term)	34
Figure 5 Research Model for Study II	61
Figure 6 The Distribution of Users' Activeness by Stage.....	64

CHAPTER 1

INTRODUCTION

Background of the Problem

The past decade has seen rapid development in health-related social media services, including patient blogs, social networking sites, and online health communities. The Harris poll (Taylor, 2010) reported that the number of adults looking for health information on the Internet increased from 71% to 88% during the last decade. An NCI-sponsored Health Information National Trends Survey (Chou, Liu, Post, & Hesse, 2011) found an increasing trend in the health-related social Internet use among cancer survivors. Online healthcare services appear to be a means to disseminate healthcare information, enhance communication, and facilitate a wide range of interactions between patients and healthcare delivery systems (Baker, Wagner, Singer, & Bundorf, 2003; Umefjord, Petersson, & Hamberg, 2003). One of the most promising health-related social media services is the widespread availability of online healthcare communities (OHC), where people with common interests or similar health conditions gather virtually to ask questions, share experiences, and provide support, as well as exchange health care knowledge (Greene, Choudhry, Kilabuk, & Shrank, 2011). Evidence in health-related social media service literature (Brandtzaeg & Heim, 2007; Johnson & Ambrose, 2006; Klemm et al., 2003; Zrebiec & Jacobson, 2001) has confirmed the widespread use of the OHCs has dramatically changed illness management and self-care, enhanced quality of life, improved decision making and increased survival time (Cline, 1999) as the OHCs are used as both a source of information and psychosocial support (Brandtzaeg & Heim, 2007; Johnson & Ambrose, 2006; Klemm et al., 2003; Zrebiec & Jacobson, 2001). Existing research on OHCs includes outcomes of support and resources for cancer survivors (Chou et

al., 2011; Hesse, Moser, Rutten, & Kreps, 2006), examination of drug use (Barratt & Lenton, 2010), health effects of e-cigarette users (Alfi & Talbot, 2013; Yamin, Bitton, & Bates, 2010), and mental health benefits (Kummervold et al., 2002) and other healthcare communities.

As IS professionals have been interested in the technologies that enable online discussion communities, they have produced a rich literature on users' continuance participation in online communities. Extant research touched on this issue has been focusing on different motivation theories (Bandura, 1995; Beach & Mitchell, 1990; Stryker, 1987; Tajfel & Turner, 2004), and suggested several powerful factors such as, experiences and needs (Armstrong & Hagel, 2000); supportive and sociable relationships (Ling et al., 2005; Turner, Grube, & Meyers, 2001); feelings of belonging (Hou, 2015; Lampe, Wash, Velasquez, & Ozkaya, 2010; Tardini & Cantoni, 2005); a sense of shared identity (Diker, 2004; Waterson, 2006); positive users' feedback (Joyce & Kraut, 2006; Lento, Welser, Gu, & Smith, 2006); and the users' perceived value-add (Al-Debei, Al-Lozi, & Papazafeiropoulou, 2013; K. Zhao, Stylianou, & Zheng, 2013). In addition, there have been few studies addressed why many initially active communities have degenerated or vanished after couples of years of development due to the low level of user activity (Millington, 2013). However, these studies mainly targeted at learning communities and consumer communities. Studies related to health communities have been focused on perspectives that are different from continuance participation: understanding the helping process of online health communities (Courtney, 2013; Marco Leimeister, Schweizer, Leimeister, & Krcmar, 2008; van der Eijk et al., 2013), social networking service support types (Loane, Webster, & D'Alessandro, 2014; Lu, Zhang, Liu, Li, & Deng, 2013; Nambisan, 2011), and reasons to provide support (Huang, Chengalur-Smith, & Pinsonneault, 2014; Nath, Huh, Adupa, & Jonnalagadda, 2016). A study by J. Zhao, Wang, and Fan (2015) touched on users' continuance intention in the context of OHC from the perspective of

factors that increase the users' willingness of co-creation with a survey method, and shed light on needs of maintaining users' ongoing participation in the OHCs.

Statement of the problem

In fact, the OHCs could better serve patients (members) only if it can attract and keep a sustainable amount of active members by focusing different periods (i.e., short-term and long-term stage). This is not only because many online communities are failing to attract enough members and to sustain themselves (Cummings, Butler, & Kraut, 2002) but also OHCs couldn't be able to benefit members and the community (Kraut et al., 2012). In the short-term, users could be interested in beneficial information and support they could get from the community; whereas in the long-term, users transition to loyalty member, as such pay more attention on quality and environment of the community. The members in OHC move through a pattern of these stages that are described and explained based on their distinguishing needs and characteristics. Thus, understanding these needs and characteristics will help scholars and practitioners better explain users' periodical behaviors.

Despite the increasingly notable role played by online health communities and a large amount of research interested in this emerging patient-driven peer-to-peer health care platform, how helpful the OHCs might for patients and how the members' participation pattern would affect the usefulness of the OHCs are still waiting to be unveiled. At our best knowledge, none of the existing research has studied OHCs from the perspective of members' different stages of membership life cycle and investigated varying factors that determine users' continuance participation corresponding to those stages. This research gap brought us two research questions: 1) What are the drivers that motivate users to survive (stay active) in the OHCs during the short-term and long-term stages? 2) How do these drivers affect users' survival during those stages? 3) What are the factors that affect users' activeness during the short-

term and long-term stages; and 4) How do these factors affect users' activeness differently during the different stages?

Objectives of the project

The purpose of this study is to identify factors that affect the users' continuance participation and to examine their different influences in the short-term and long-term stages survival and activeness in the OHCs. Specifically, we attempt to identify factors (i.e., *seeking behaviors and corresponding supports*) that affect the users' continuance participation in the different stages at OHC. Social support (Langford, Bowsher, Maloney, & Lillis, 1997) has long been proved as a strong motivation that drives users to stay in health community because it promotes health (Berkman & Glass, 2000; S. E. Cohen & Syme, 1985). Literature (Coursaris & Liu, 2009) shows that informational support and emotional support are ranked the first and second place of users' purpose of social support exchanges in the online health community. In this study, we investigate users' initial goals, including *information seeking* and *emotional seeking*, and map these goals into the *informational support* and *emotional support* they received from the OHCs to predict the users' short-term vs. long-term survival. We believe the way how the member who started the thread interacted with other user is an important factor that could indicate the users' survival time as well.

In addition, we also attempt to understand the changes of users' expectation and engagement over time in terms of short-term and long-term activeness. Especially, we believe the users are motivated to be active in the online health community when they expected that benefits of engagement outweigh the costs. There are different types of benefits including social support, social attachment, and recognition.

These are the important factors for community members to keep involved in the community after they moved into the short-term stage. The organizational commitment, enacting an engagement or obligation that prevents employees from leaving the organizations, has long been studied by scholars to predict work variables such as turnover, job performance and altruistic behavior (Porter, Steers, Mowday, & Boulian, 1974; Williams & Anderson, 1991). One characteristic of long-term users is their altruistic behavior, meaning users are no longer staring at exacting but transitioning into dedicating. We believe that although satisfied social support will be the dominant factor leads to users' short-term activeness, its influential power may alleviate in predicting their long-term activeness unless the users' commitment is developed during his/her participation.

Our research makes two major contributions. First, we identify the factors that determine users' short-term vs. long-term survival. Specifically, we propose a new construct, the initial goal, to social support theory. Results show that information seeking and emotional seeking goal, and their corresponding support will drive users into different stages of their membership life cycle. Additionally, appropriate self-interaction also leads to long-term survival. Second, we identify the factors that lead to users' short-term and long-term activeness. Our study compares the users' participation behavior during the different stages and predicts their post-stage activeness based on expectation-confirmation theory. Our findings show that the social support and recognition in the initial stage play important roles in the short-term activeness, whereas the social attachment in the short-term stage increases its impact on the long-term activeness.

CHAPTER 2

LITERATURE REVIEW

The success of an online health community (OHC) depends on the members' loyalty in terms of continuance participation (Brandtzæg & Heim, 2008); in other words, an online community will not survive without lasting user motivation and participation (Faraj & Johnson, 2011). As such, it is necessary to understand the people who will use the service, the goals or tasks they have, and their context of use (Hackos & Redish, 1998), since the goals or tasks users have in online communities are often seen in relation to motivational issues (Brandtzæg & Heim, 2008). Fail to attract enough members to sustain themselves has been a primary reason that many online communities stall (Cummings et al., 2002). Motivation theory has guided researchers to study factors that inspire people to take part in an online community (Waterson, 2006). Existing literature on users' loyalty from the perspective of motivation suggested several powerful factors: people with shared interest; experiences and needs; supportive and sociable relationships; strong social feelings of belonging; and a sense of shared identity (Diker, 2004; Waterson, 2006). There is also a well-developed research stream that used self-concept theory to explain the phenomenon of contribution to online communities, which includes social identity theory (Stryker, 1987; Tajfel & Turner, 2004), self-presentation theory (Beach & Mitchell, 1990), and self-efficacy theory (Bandura, 1995).

A stream of literature touched on the issue from the perspective of communities' sustainability, suggesting that online communities provide benefits and experiences that members seek in order to gain end-user loyalty (Brandtzæg & Heim, 2008; Ridings & Gefen, 2004). Researchers have proposed rich

descriptions of design features to increase members' likelihood of joining and remaining in online communities, for instance, (Lazar & Preece, 2002; Ling et al., 2005; Phang, Kankanhalli, & Sabherwal, 2009). These studies provide rich insights into online community design and management, but neglect the role of members' individual characteristics and goals and how these will affect their decisions on continuing participation.

Other studies have made solid theoretical contributions to the literature by investigating online communities' phenomena from an individual level of analysis. These studies suggested that the reasons individuals participate in online communities include being attracted by community benefits (Ridings & Gefen, 2004), a sense of reciprocity (Hall & Graham, 2004; Wasko & Faraj, 2000), and a desire to help the community (Constant, Sproull, & Kiesler, 1996; Lakhani & Von Hippel, 2003). However, these studies mainly focused on personal utilitarian motivations of knowledge sharing (Hall & Graham, 2004; Wasko & Faraj, 2000) but neglected the hedonic factors that may be very important in the context of online communities (Faraj & Johnson, 2011).

Last but not least, previous studies on users' motivation rely on survey method to investigate users' intentions and behaviors. Studying on probability sampling from large populations, survey method might suffer from inadequate coverage of population and data errors due to non-response or low-response. Secondly, survey method often used in studies that are not time sensitive. For an instant, the survey result usually shows the opinions of the survey objects at the moment of taking the survey. It is static, and do not capture the trajectory of any changes of the subject over time. The following table summarizes some important studies on users' participation in online communities.

Table 1 Studies on Users' Participation in Online Communities.

Literature	Theory and/or Method	Findings
Hou, 2015	An ethnographic case study	Users' Feelings of belonging and a sense of shared identity are key motivating factors
Al-Debei, Al-Lozi, & Papazafeiropoulou, 2013	Theory of Planned Behavior	User's perceived added-value motivates their continuance intention and behavior of using SNS
K. Zhao, Stylianou, & Zheng, 2013	IS post-adoption and Theory of Reasoned Action A survey based methodology	Users' previous usage and perceived benefits are indicators to continuance participation intention
Joyce & Kraut, 2006	Interaction and commitment Content analysis	Positive feedback is a motivation to users' participation
Ridings et al. 2004	Social identity theory open-ended question	Supportive and sociable relationships are key motivations for users' participation

The above-mentioned studies made excellent contributions to online community research.

However, they are focusing on general communities such as learning communities and consumer

communities. The online health communities have their own features other than learning communities. For example, instead of targeting at informative support which is the top priority in a learning community, users may give more credits to emotional support in an online health community, because it helps users to relieve stress and enhance the quality of life. As such, we narrow down our literature review to online health communities.

These studies focused on perspectives that differ from continuance participation, such as understanding the helping process, the different types of social support, the reasons to provide support and as well as the benefits of using the OHCs. A study by Zhao(K. Zhao et al., 2013) has touched on users' continuance intention in the context of OHC from the perspective of factors that increase the users' willingness of contribution. Zhao's research shed light on needs of maintaining ongoing participation in the OHCs. As a matter of fact, the OHCs could better serve patients (members) only if it can attract and keep a sustainable amount of active members.

Table 2 Studies on Online Health Community

Literature	Theory and Method	Findings
Nath, Huh, Adupa, & Jonnalagadda, 2016	The descriptive analysis	The reason why people share health information online.
J. Zhao, Wang, and Fan, 2015	A survey based method	The factors that increase the users' willingness of co-creation and continuance participation intention in OHCs
Huang, Chengalur-Smith, & Pinsonneault,	Social support theory	The companionship activities that can increase participation in support

2014		exchange behavior in OHCs.
Huang, Chengalur-Smith, & Pinsonneault, 2014	Social support and Consumer value Theory	The benefits that the OHCs can provide to consumers.
Lu, Zhang, Liu, Li, & Deng, 2013	Text mining method	A text clustering method used for health-related hot-topic detection.

To our best knowledge, the study on the behavior patterns of users' continuance participation in online health community has been lacking. In this study, we attempt to understand the motivations that drive online health community users to join, stay in and participate in the community. Users may have different priorities in their participation during the different stages of their membership life cycle. For example, in the short term stage, users may focus on what they can obtain from the community, while in the long term stage, they may focus on what they can provide to the community. Our key interest of this study is to understand what are the factors that affect users' continuance participation behavior in terms of survival time and activeness during the different membership life cycle, and why the factors work differently in different stages.

CHAPTER 3

STUDY DESIGN

The process of a user joining and committing to an online community usually includes the following steps (Butler, Bateman, Gray, & Diamant, 2014). First, a user views through the online community after it is introduced to the user, and then he/she may get attracted depending on the congruency between his personal expectations and the community's topics and activities (Ridings & Gefen, 2004; Wasko & Faraj, 2000). Potential members' expectations can be developed at the first join if the users have very clear purposes when they were introduced to the community or be developed by reading formal descriptions or official documents of a community (Butler et al., 2014). We define the users' purposes or expectations at the first join as the *initial goal*. These goals could be obtaining information and knowledge or releasing mental stress and getting emotional support. Second, the user participates in the activities in the online community, and the user will interact with other members in the community and receive feedback or support. This leads to a selection process which refers to the ongoing evaluation of consistency between the user's initial goal and the received support (Ryan, Sacco, McFarland, & Kriska, 2000). This continual reassessment may change users' engagement with community members in the discussions because of the changes in their expectations and satisfactions (Jin, Lee, & Cheung, 2010). Third, while members continually update their expectations and evaluations of their goals and support, users may grow in two separate ways. One group of users solely remains their initial expectation of receiving support and may reduce their activeness as they expect that the community's future discussions will not provide them with more information or knowledge or what they

needed (Andrews, 2002; Ransbotham & Kane, 2011). In contrast, another group of users develops the emotional attachment to the online community. Besides of receiving support, they are also interested in providing support to other members, and therefore, yield high activeness in the long-term.

To understand the users' participation trends and behavior patterns, this study attempt to investigate users' posts in different stages of the membership life cycle. It starts with investigating users' motivation of the initial acceptance and then gets into their loyalty development from short-term to long-term. There are two studies in this research. The first study attempts to predict the users' survival time in terms of being active during the short-term stage or the long-term stage based their initial stage activities. The second study attempts to identify the factors that affect users' activeness during the short-term and long-term stages, and why the same factors work differently in the different stages.

In the business and marketing field, theories of customer life cycle and membership marketing life cycle are introduced to help organizations to maintain loyalty customers (Dick & Basu, 1994; Hallowell, 1996). Although these theories claim different names of customer member stages, in general, they all include three key phases: awareness, engagement, and loyalty. Adopted from these theories, we consider three different stages of the membership life cycle, which corresponds to the three general steps that a user joins and commits to an online community.

Table 3 Description of Membership Life Cycle Stages

Membership life cycle Stage	Description
Initial stage	First 2 weeks of being a member
Short-term stage	3 months after the initial stage
Long-term stage	Users' life time after the short-term stage

The *initial stage* is the first 2 weeks of a user being a member of the OHCs. In online community literature (Burke, Marlow, & Lento, 2009), the first 2 weeks of being a member are considered the most important time span that the “newcomers” (Ashforth, Saks, & Lee, 1998) decide to stay or leave. A member can make the decision of stay or leave at any time during his/her membership lifecycle.

The *short-term stage* begins with the third week until the second week of the fourth month of being a member in the OHCs. It covers the following three months after the *initial stage*. We define the *short-term stage* is the time that a member is accepted the OHC as an interesting and useful community which he/she wants to engage with and hopes to get more knowledge and support from the community.

The *long-term stage* begins with the third week of the fourth months until the end of a member’s life time in the OHCs. Thus, we define the *long-term stage* is the time that a member has developed trust and a sense of belonging to the community. Besides of requesting support from the community, the user wants to contribute to the community and provides support to others as well.

In the following section, two studies are conducted. One study is about the members’ short-term and long-term survival, the other one is about the members’ short-term and long-term activeness. In each study, it will start with a section of theory building and hypothesis testing, and then followed by the research methodology, in which it contains data collection, data description, data analysis, and model results. The third section in each study is the findings and discussion. The last chapter of this research is the conclusion.

CHAPTER 4

STUDY I: SHORT-TERM VS. LONG-TERM SURVIVAL

Theory building and hypothesis development

Initial stage participation clue for short-term vs. long-term survival

In an OHC, the *initial stage* is the time period that a user is attracted by the community and initially participates in the activities of the community. In this stage, the users' motivation of their initial acceptance comes from the expectation of getting what they need from the online health community. The participation of initial stage is related to the selection process where the users continuously evaluate the consistency between their initial goals and the support they received from the community. Users' experience of whether their goals have been met during the initial stage will determine their decision to further stay or leave.

The *short-term survival* means that the user is active in the short-term stage, yet, inactive in the long-term stage. The *long-term survival* means that the user is still active in the long-term stage.

Motivation and initial goal: information vs. emotional seeking

Originating from consumer behavior theory, utilitarian and hedonic motivations (Laurent & Kapferer, 1985; Park & Young, 1986) are two dimensions of an individual's overall perceived value that can drive specific outcome behavior. The term utilitarian is more task-oriented in nature, whereas the term hedonic is related to entertainment, fun-seeking, and other emotional desired behavior (Constant et al., 1996). Recently, researchers have addressed the role of both utilitarian and hedonic values in the study of online service usage (Cotte, Chowdhury, Ratneshwar, & Ricci, 2006; Hong & Kim, 2004; M.

K. Lee, Cheung, & Chen, 2005; Y. Lee, Chen, & Ilie, 2012). Utilitarian value is objective and task-focused with the goal of achieving a pre-determined task, which in OHCs refers to the users' expectation of obtaining required information and knowledge. As we mentioned earlier, the process of joining and committing to an online community (which also applies to the OHC) includes initial attracting by, participating in, getting support from, matching initial goals with, and committing to the OHC. It begins with utilitarian motivation which is considering whether or not they can achieve their initial goals by participating in the OHC.

However, the task-oriented motivation could only last for a certain length of time period. The users with information or experience seeking goals post questions when they join the community. Yet, they probably stop engaging with others if they are only focusing on requesting and receiving information. Their interests may not last if they cannot get proper answers, or once they have answers to all their questions. At a certain time, users would expect that in the future participation, they cannot get more information or support as they already gain the most knowledge and experiences in the field. As time passes by, the users with goals of getting information or support may lose their interests of continuance participation. Unlike utilitarian value, hedonic value (Zhang, 2013) focuses on the emotional desires fulfilled through participation, including enjoyment and comfort. Consumers' behavior is often at least partly driven by emotional desires rather than cognitive deliberations (Hsu & Chiu, 2004). Users' behavior in the online community is evoked from feelings of pleasure, joy, and other positive emotions (M. K. Lee et al., 2005; Venkatesh, Speier, & Morris, 2002). Mental health and stress relief is another crucial component of the OHCs. Feeling comfort and sympathy as well as a sense of belongingness can be a strong emotional driver that leads to users' long-term activeness in the OHCs.

The *Initial goal* refers to the user's purposes and expectations of joining the OHC when he/she first knows and gets attracted to the community. We consider two types of users' initial goals: information seeking and emotional seeking.

Users with *Information seeking goal* are primarily looking for answers to issues they had/experienced or asking questions on general knowledge for self-management. This kind of post aims at finding information and answers. An example of a post with information seeking goal is as follows:

"I have recently been diagnosed with osteoarthritis which is causing me a lot of pain. I am also having the highest morning numbers ...between 180 and 250... even when I go to bed with a good number. Could the pain be causing the elevation of my glucose?"

Utilitarian value is a task-oriented function, which is achieved by receiving the information that the seekers were desired to obtain. In the OHC, the information related discussion among users serves as an information source that enhances knowledge and competency (Gruen, Osmonbekov, & Czaplewski, 2006). The information and knowledge received from the discussion can help information seekers to improve their decision making. Utilitarian motivation is the force that directs information seeker towards their goal of receiving answers. Users with the goal of information seeking assess the help they can get from the community to solve their problems. With the direct impact of solutions, information seekers are driven by utilitarian motivation.

Users with *emotional (support) seeking goal* focus on sharing personal experiences or calling for others' experiences with a certain topic, such as experiences on illness management. In this kind of posts, users are more interested in discussing personal experiences and emotional feelings other than finding solutions. An example of a post with experience seeking goal is as follows:

“New pumper (6 weeks), had dinner 7 pm, took a bolus, subsequently had a snack soon after without a bolus because it was relatively close to dinner. I woke a to a Bg of 238 at 2am. Let the bolus wizard calculate the appropriate amount (no food assigned). Checked bg at 5am to find a bg of 51, had some juice and carbs (banana). I guess some fine tuning is in order.”

The emotional seeking posts focus on emotional desire fulfilled by participation itself, as such related to hedonic values. The OHC is not only the users' knowledge source but also the platform for stress relief and emotion-focused coping (Josefsson, 2005; Lau & Kwok, 2009). Van der Heijden (2004) suggested that with the effect of the emotion-focused coping of an information system, perceived usefulness loses its dominant predictive value in favor of hedonic value, such as enjoyment. Agree with Van der Heijden, we believe that hedonic motivation included but not limited with feeling comfort and sympathy is a stronger emotional driver that lasts longer than utilitarian motivation. As such, we formalize Hypothesis 1 as follows.

Hypothesis 1-1: *User’s initial goal likely leads to long-term survival when he/she seeks peers’ experience (emotional support seeking), whereas it likely leads to short-term survival when the user seeks peers’ information (information seeking).*

Motivation and social support: informational vs. emotional support

In the social science community, there has been the recognition that social relationships are essential to personal health and happiness. Social support (Cobb, 1976; S. Cohen & Wills, 1985) is one of the most important functions of social relationships that is always intended by the sender to be helpful, thus distinguishing it from intentional negative interactions. Social support (Shumaker &

Brownell, 1984) is defined as an exchange of resources between at least two individuals. Extant studies over the past few decades indicate that social support can protect people from the adverse effects of stress through stress buffering (S. Cohen, 2004). Cobb (1976) believes that supportive interactions (providing and receiving social support) among people protect against the stress, and proposes the buffering theory to explain the positive relationship between social support and patients' health condition (S. Cohen & Wills, 1985). Social support distinguishes between different types of support by scholars (S. Cohen & Wills, 1985; Himle, Jayaratne, & Thyness, 1991; Zimet, Dahlem, Zimet, & Farley, 1988). The social support that commonly studied by scholars in health-related services (Berkman, Glass, Brissette, & Seeman, 2000; Yan & Tan, 2014) are informational support (e.g., knowledge, information and advice), emotional support (e.g., personal experiences, empathy/sympathy, comfort and encouragement), and companionship (e.g., chatting and humor). Particularly, informational and emotional support have been found as the most frequently offered types of support as well as the types that are deemed most helpful by participants (Guthrie & Kunkel, 2016). Informational support involves the provision of advice, suggestions, and information that a person can use to address problems. Emotional support is associated with sharing life experiences. It involves the provision of empathy, love, trust and caring.

Informational support: refers to the provision of advice, suggestions, and information that a person can use to address problems. Members in OHCs exchange informational support about the course of their disease, treatments, the usage of devices, side effects, doctor visiting experience, and financial problem and other burdens (Y.-C. Wang, Kraut, & Levine, 2012). An example of the informational support post is as follows:

“If you are interested in purchasing a Dexcom, they will do trials. I did a trial for an entire month before I bought it (though I think the rep I was dealing with was really nice, not sure all of them would let someone trial one for so long). In my case, it was to make sure that my body could tolerate the sensors, given the issues I’ve had with infusion sets.”

Informational support has been the most frequently addressed support type in the online health community, as well as other types of online help groups and communities. Scholars believe that online health communities act as health knowledge repository to patients, especially to those with chronic diseases.

Emotional support: refers to the provision of empathy, love, trust and caring. This kind of posts is usually associated with sharing life experiences with the purpose of comforting others. Members in OHCs can receive emotional support directly by messages of caring and concern; or indirectly, through comparisons with others who have had similar experiences (Bambina, 2007; Y.-C. Wang et al., 2012). An example of the emotional support post is as follows:

“Having battled with depression most my life, what works for me is that eventually the fog will lift and I will feel better. There are many painful lonely walks. And then life is better again ”

Emotional support is especially helpful to patients with mental problems such as stress and depression. Stress is often described as a feeling of being overwhelmed, worried or run-down. Baum (1990) defined stress as an “emotional experience accompanied by predictable biochemical, physiological and behavioral changes” Patients live with chronic diseases are usually forced to cope with different levels of stress. An extreme amount of stress can have health consequences and adversely

affect the immune, cardiovascular, neuroendocrine and central nervous systems (N. B. Anderson, 1998). Emotional support that comes from peers can arise patients' resonance, and the feeling of being understood will release the stress of social isolation or loneliness that comes with the illness (McCorkle, Rogers, Dunn, Lyass, & Wan, 2008).

Informational support and emotional support have been proved to have a positive relationship with users' activity and survival time in online health community (X. Wang, Zhao, & Street, 2014). Studies (Biyani, Caragea, Mitra, & Yen, 2014; Y.-C. Wang et al., 2012) have long been interested in how informational support and emotional support affect users' behavior in OHCs. Emotional support (Y.-C. Wang et al., 2012) has been found more powerful influence compared to informational support in the member retention and commitment. Informational support (Meier, Lyons, Frydman, Forlenza, & Rimer, 2007) is undoubtedly the number one frequently sought social support in the online health community. However, it is less lasting than emotional support. As such, we formalize hypothesis 2 as follows.

***Hypothesis 1-2:** User's received support type likely leads to long-term survival when he/she receives emotional support, whereas it likely leads to short-term survival when the user receives informational support.*

Motivation and support matching

Social support is the perception or actualization of care or assistance from a social network (Cummins, 1988). Social coping refers the seeking of social support in the presence of stressful situations. Prior studies show social support and coping enhance patients' satisfaction by providing the problem solution and regulating emotion (Earnshaw, Lang, Lippitt, Jin, & Chaudoir, 2015). Satisfaction

refers to “the psychological state that is related to and resulting from a cognitive appraisal of the expectation performance discrepancy (confirmation)” (Bhattacharjee, 2001b). If the performance is higher than/or equal to expectations, the users would acquire greater confirmation, which in turn positively influence customer satisfaction and continuance behavior. However, higher expectation and/or lower performance will lead to disconfirmation, dissatisfaction, and thereby discontinuance behavior.

In the online health community, the members who posted questions would want to get answers or at least relative information about that question. However, sometimes, the reply posts didn’t provide useful information or didn’t relate to the question. The following example is a question post that is looking for answers about what insurance is most OmniPod friendly. The question post is as follows.

“My husband currently does manual injections many times a day but would love to start using the OmniPod. We are currently in the process of signing up for a new health care plan through the marketplace. Can anyone suggest healthcare companies or plans in Florida that are most OmniPod friendly? I have done a ton of research online and calling insolent as well as all of the insurance companies but nobody can give me definitive answers as to whether the pod will be covered and if so what the cost would be. I am very hesitant to sign up for a new health care plan before knowing the costs as the Omnipod was still extremely cost prohibitive with the "healthcare coverage" we received from our last health care plan made.”

There were 38 reply posts from 19 members in the online health community. Some members suggested the insurance companies they liked, some members suggested some insurance company for

the lady who asked the question to call, and some members shared their experiences with the insurance company. Some of the replies are quoted as follows.

“I think you might want to try some other insurance plans. You might compare Kaiser plans with Cigna and a couple of others.” (replier#1)

“FreeStyle has a program, I think it's called Promise, where you'd only pay \$15/month no matter what your insurance is as long as you have insurance.....”(replier#2)

"When I complained about this to my insurance company, They said I should contact Insulet, Minimed, Dexcom directly and ask them to find out the cost with insurance companies. Apparently, the rates vary according to the contract of each insurance company" (replier#3)

However, there are also a few reply posts didn't provide useful information.

“(T)he whole insurance thing is ridiculous if not deadly sorry that's my opinion” (replier#4)

“We all clearly need insurance...because the drug/medical equipment is extremely expensive”(replier#5)

It is important to the user whether or not he/she can get the information he/she was looking for. In an information seeking post, if too many reply posts are off-topic or not useful, the user might be disappointed by the community, and thereby, decide to not come back to the community.

To investigate why users decide to stay or leave the OHCs, we need to consider the users' post-adoption psychological motivations, for example, satisfaction and confirmation (Jin et al., 2010), as these factors are proved to be stronger predictors of continuance behavior in prior IS literature (Bhattacharjee, 2001b). Users' expectation of participation is represented by the initial goal, and the performance is expressed as the received support. When the type of support the users received matches what they sought to, it is very likely to lead to a higher short-term activeness due to their satisfaction and confirmation. As we discussed earlier, when a member first joins the online health community, he/she engaged in the activity by reading, initiating and answering posts with the goal of getting some types of help. A member with the goal of information seeking might be more likely to be satisfied with the community when he/she gets the same type of support. The same as the members with the goal of emotional seeking. As such, we believe the users' evaluation of the consistency of their initial goals and received support will have a strong impact on users' short-term vs. long-term survival. As such, we formalize Hypothesis 3 as follows.

Hypothesis 1-3: *A user is more likely survived to the long-term stage than the short-term stage when the type of support he/she received matches his/her initial goal.*

Motivation and self-interaction

The online health community provides a platform for people with similar health conditions to connect and communicate with each other. An effective communication is a key for users to receive what they are looking for. As one type of Computer-Mediate Communication(CMC) method, the discussion forum of an online health community provides some advantages (Braithwaite, Waldron, & Finn, 1999; Turoff, 1991) such as disregarding time and place dependence (e.g. Users can provide answers whenever and wherever they are available), facilitating the archive of information (e.g. more

users can provide their opinion or suggestion), and breaks down the barriers of communication (e.g. shyness, physical limitations, or privacy concerns). However, the big concern of CMC is the limits of the richness of communication compared with face-to-face communication. Interaction is the key in communication. However, due to the asynchronous nature of online discussion forum, it is sometimes hard to get the necessary explanation to help the reader better understand the question in a post. The misunderstanding might happen due to wrong interpretation of the meaning of the words or the tone of the sentence. A good way to enhance communications in online health community is to interact with other users, which involves replying to the reply posts in the threads they started. This may help the members who answer the question better understand what type of information the thread owner was seeking. The following example shows a diabetic lady who found out about her first-time pregnancy and was worried about her blood sugars. Let's take a look at how she interacts with other members.

“Hi everyone, I just found out I am finally pregnant (about 5 weeks) My A1c is 5.7 after months of getting it down, and I have been trying to conceive for about 6 months (had a chemical pregnancy a few months ago. But anyway, just been feeling so worried that something like that will happen again because it's impossible to keep it perfect all the time! It's so hard not to beat myself up over every high or low but I am literally scared to put a carb in my mouth because it never stays stable. I had it down a few weeks ago and now I think the hormones are throwing it all out of wack! I have a pump and cgm but it's still challenging. Just wanted to know how you dealt with all that. Also are lows bad for the baby too? I know highs are. Any advice for getting through this? Thanks!!”

A member(replier#1) replied the post:

"I actually joined this site awhile ago when I found out I was pregnant, which was a surprise and unplanned. I felt the same way as you and was so scared every day, but I had a beautiful little boy who is healthy.I actually ended up having him a month early. No need to stress just do the best you could!"

And the thread starter replied:

"Thanks so much! It is so nerve wracking but I am doing everything I can so I guess you're right- I just have to go with my instincts and do the best I can- thanks again :)"

Another member (replier#2) replied the initial post:

"Hi! I'm 15 weeks into my second pregnancy. I can totally relate to the feeling and for me it never totally went away even with this pregnancy, but somehow I learned to cope with it better. I have never managed to get an A1c below 6, but hang out between 6 and 6.5. One thing to know is that with both pregnancies for me the first weeks were totally unpredictable. Which meant that I had really high highs (like 400s), which never happened for me later in the pregnancy. Everyone is a bit different,"

The thread starter replied:

"Thank you so much and congrats on your pregnancy too! It can be so overwhelming but so far people have been super helpful. One thing I am not used to is feeling fine at 50...no symptoms whereas a sugar of 80 used to make me shake. ... Also just curious, how often did you send in your numbers to your doc? These days I am s(p)ending every day but wondering if that tapers off. Thanks!"

And then the member (replier#2) replied again

“Yes, there are so many changes to deal with. I meet my endo once a week,..... Sometimes I send her my numbers mid-week, but mostly the once a week adjustments are enough except when I hit major insulin resistance around week 22. Send your numbers as often as you feel you should, especially in the beginning!”

In the meanwhile, there are other reply posts by different members in the community, and the thread starter also replied some of the other reply posts to have a deeper conversation or to express her appreciation. This example shows a nice interaction among the thread starter and the repliers. The user posted this thread on the same day she created her account. It is a very efficient communication. The thread starter received the support she sought. As expected, this user survives to the long-term stage.

In the online health community, there are two types of communication patterns of the users. One type of user asks questions and reads the answers provided by other users. They might also try to combine other resources by searching questions in other knowledge repositories. This type of user sometimes even didn't go back to check the reply posts to their question if they found what they need from other resources or even if they didn't. The other type of user is more active in communication. They would come back frequently to check if anybody had answered their questions or not and would interact with the person who answered their questions by asking more detailed or related questions or expressing appreciation. This type of user is usually more active in the online health community and tends to survive to the long-term stage. As such, we formalize hypothesis 4 as follows.

Hypothesis 1-4: *A user is more likely survived to the long-term stage than the short-term stage if he/she appropriately engages (self-interaction) in the discussion of the posts he/she has initiated.*

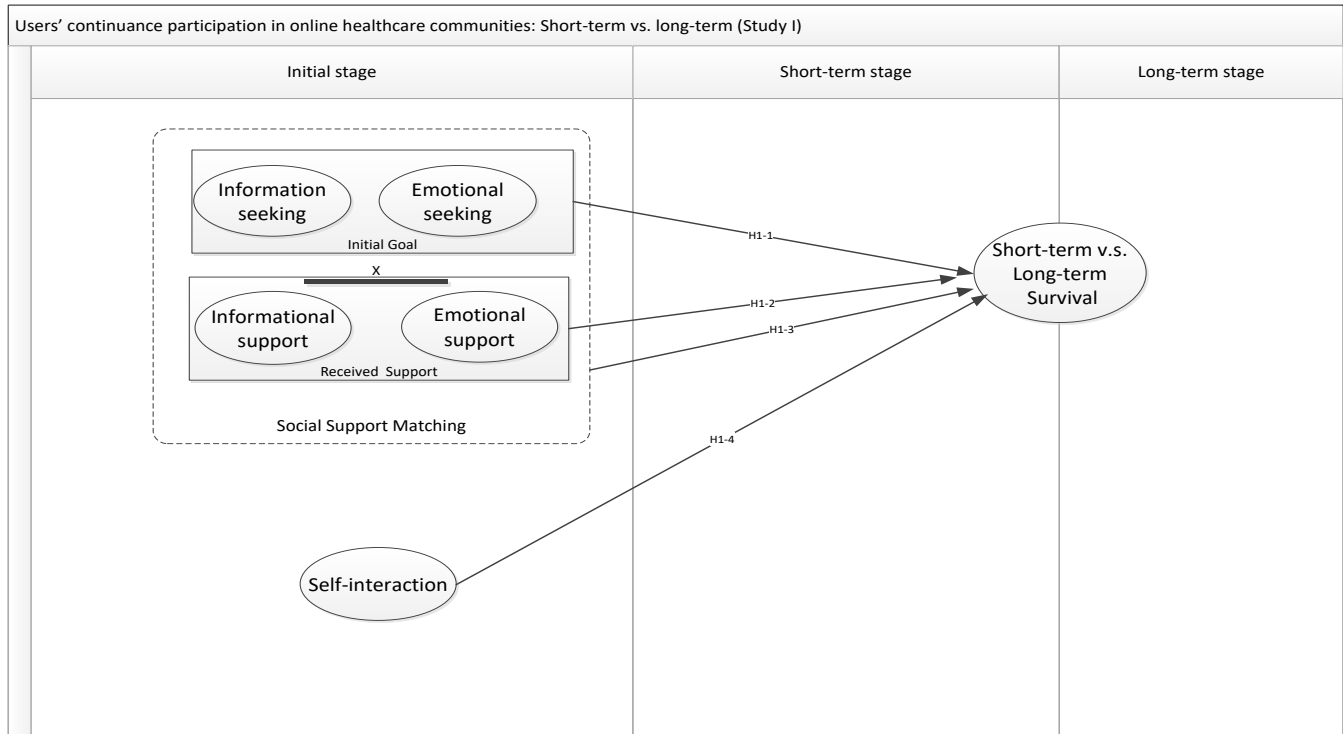


Figure 1 Research Model for Study I

Research Methodology

Model Measurements

Tabel 4 Constructs and Measurements

Constructs	Description	Measurement
Short-term survival	The user is active in the short-term stage, but inactive in the long-term stage.	$f(x) = \begin{cases} 0, & \text{if active short term;} \\ 1, & \text{if active long term;} \end{cases}$
Long-term survival	The user is active in the long-term stage.	$f(x) = \begin{cases} 0, & \text{if active short term;} \\ 1, & \text{if active long term;} \end{cases}$
Information seeking	Looking for answers to issues they had/ experienced or asking questions	The percentage of information seeking posts of a user

	on general knowledge for self-management	
Emotional seeking	Look for comfort by sharing personal experiences, or calling for others' experiences with specific topics.	The percentage of emotional seeking posts of a user
Informational support (Adjusted informational support)	The provision of advice, suggestions, and information that a person can use to address problems	<p>The percentage of informational support posts of a user;</p> $f(x) = \begin{cases} x/6, & \varphi(x) \leq 6 \\ x, & \varphi(x) > 6 \end{cases},$ <p>where x is the percentage of the informational support received by a user, and $\varphi(x)$ is the count of reply posts of the user's initial posts</p>
Emotional support (Adjusted emotional support)	The provision of empathy, love, trust and caring	<p>The percentage of emotional support posts of a user;</p> $f(x) = \begin{cases} x/6, & \varphi(x) \leq 6 \\ x, & \varphi(x) > 6 \end{cases},$ <p>where x is the percentage of the emotional support received by a user, and $\varphi(x)$ is the count of reply posts of the user's initial posts</p>

Informational support matching	The degree to which the support type received from a thread matches the information seeking	The percentage of informational support multiply by 1 if initial post is information seeking; multiply by 0 if initial post is emotional seeking
Emotional support matching	The degree to which the support type received from a thread matches the emotional seeking	The percentage of informational support multiply by 0 if initial post is information seeking; multiply by 1 if initial post is emotional seeking
Support matching	The combination of informational support matching and emotional support matching	Informational support matching + emotional support matching
Self-Interaction	The degree to which the user who initiates the thread engage in the discussion. The ratio of self-reply posts to all the reply posts (Self-interaction).	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x - \mu}{\sigma}\right)^2}$ <p>Where μ is the mean of the self-interaction, and σ is the standard deviation of the self-interaction</p>

Data collection

Of all the health information searched online, diabetes is one of the most common searched disease-related topics. In 2013, it was estimated that over 382 million people throughout the world had diabetes (Melmed & Williams, 2011). As a chronic illness, diabetes requires continuing medical care and patient self-management education to prevent acute complications and to reduce the risk of long-term complications (AmericanDiabetesAssociation, 2009). Online diabetes communities can help

patients with self-education and psychosocial support. Previous studies on online diabetes communities focused on topic discovery and categorization (Franklin, Greene, Waller, Greene, & Pagliari, 2008; Ravert, Hancock, & Ingersoll, 2003), and health outcome benefits (Bond et al., 2006; Franklin et al., 2008; Savolainen, 2011). However, to our knowledge, no study on online diabetes communities focuses on users' continuance participation by investigating users activeness and behavior pattern from the different membership life cycle stages and examining the factors that affect users short-term and long-term survival.

Tudiabetes.org is an OHC that aims at providing a platform for people who have diabetes to get in touch with others, help each other out, and educate themselves. To validate our research theories and models, we collected data from the "Tudiabetes.org" community using a Python web crawler. We stored the data in MongoDB, a Non-SQL database system. Up to March 2016, there were 47,412 discussion threads and a total of 274,503 discussion posts in the forum. On average, there were 6 reply posts for each initial post. There were 40,966 users in the user profile data set. The average stay length of a user is 181 days. Our database contains all the information on the website that can be publicly accessible, including thread, users' profile and users' statistics. We write python code to retrieve the data from our database based on our need. In order to get a close investigation of the users' posts and behavior pattern, we select a 2-year study period from January 1, 2013, to December 31, 2014. The data set includes all the users who joined during the study period.

Figure 1-2 shows the data processing for the study.

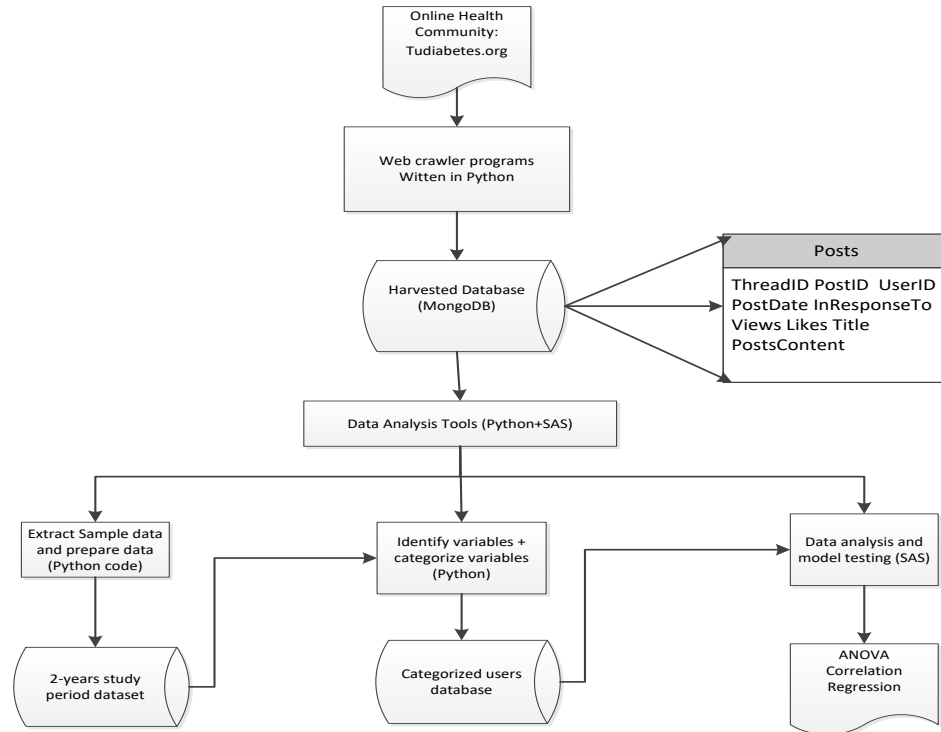


Figure 2 The Data Processing

During the study period from January 1, 2013, to December 31, 2014, there were 1855 new members who joined and posted at least one post on the discussion forum on the Tudiabetes.org during the study period. The shortest stay length is less than 1 day (represented by 0 day in the data set), in which case the members registered and submitted one or more post on the same day, but never logged back in or never posted other messages even if they came back later days. The longest stay length is 1152 days, in which cases the members are still active in the community at the time we collected the day. On average, the members' stay length is 178 days. It is very close to the average stay length of 181 days of the whole population. As such, we believe the data sample is representative. The descriptive data for our selected study period are as follows.

Table 5 The Users' Stay Length

Variable	Label	N	NMiss	Total	Min	Mean	Median	Max	StdMean
Stay		1855	0	329807	0	177.794	52	1152	5.64410

The following figure shows the frequency distribution of users' stay length. There is a huge amount of the users who joined the online health community but became inactive after the first two weeks. Literature in the online community study suggests that the first two weeks are the time that a member evaluates the community and makes the decision on accepting the community or not. It is similar to the free trial period for the charged membership in business and marketing field. It is reasonable to have a big number of member drop at this period. After the first two weeks, members entered into a relatively stable period of time, which we called the short-term stage. It is the following 3 months. As shown in the graphic description, after 3 months, the user finally gets to a more stable stage, which we called the long-term stage. As shown in the figure, the online health community will continuously face losing of members. It is a normal phenomenon, and consistent with customer life cycle theory. New members will come in and offset the loss of losing old members. As long as the community retains a certain amount of active users, the community is healthy and successful(Butler et al., 2014).

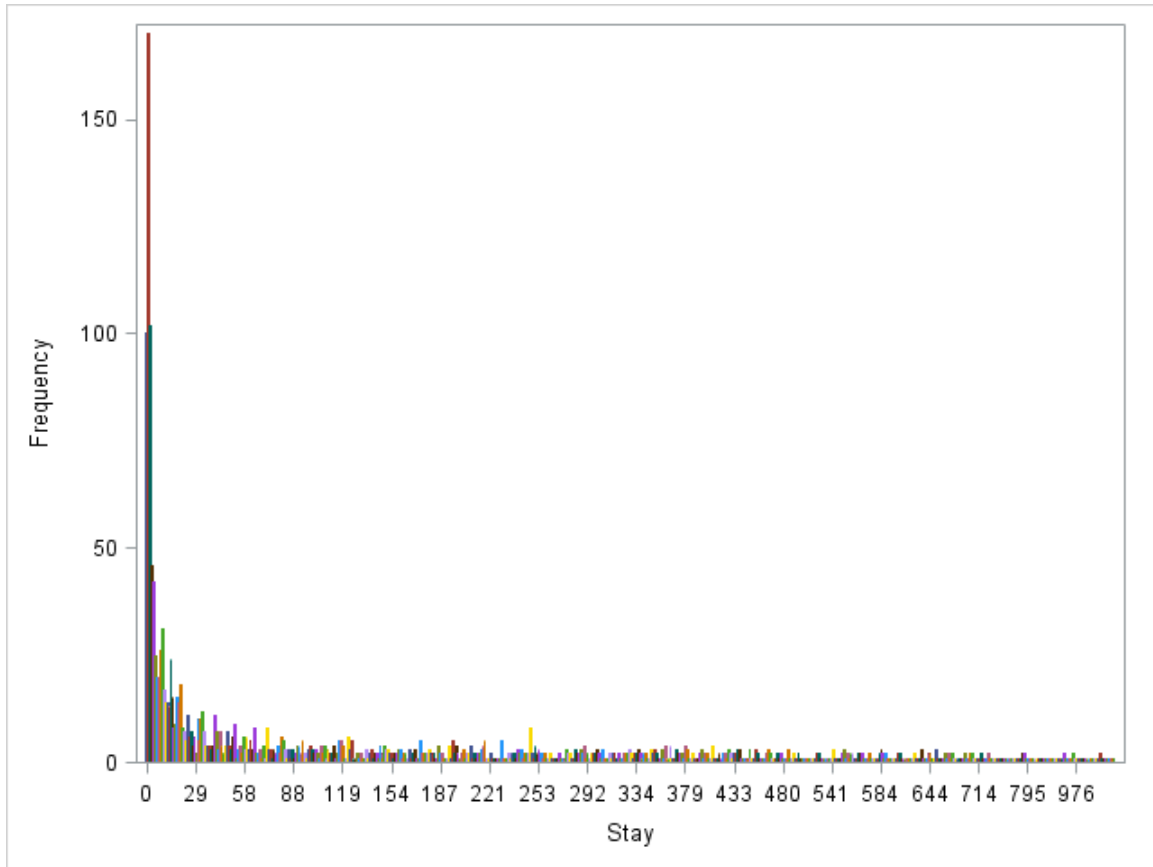
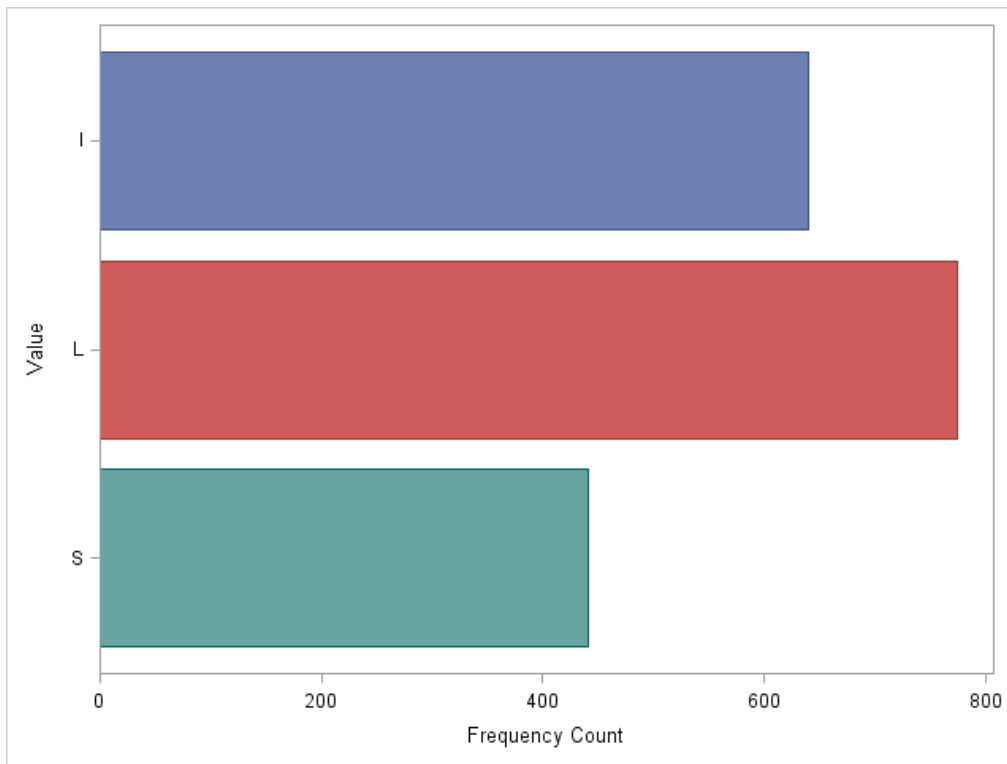


Figure 3 Users' Stay Length and Frequency Distribution

As we mentioned earlier, the time span of the first two weeks is defined as the initial stage of the membership life cycle. In the marketing and business domain, scholars and practitioners frequently study customer loyalty by their life cycle (customer life cycle or membership marketing life cycle). There are different theories and different stages, yet, all of them includes three key phases: awareness, engagement, and loyalty. We define these three stages of the users' membership life cycle in an online health community as the initial stage, the short-term stage and the long-term stage. Table 4 and figure 4 shows the users' statistics by their membership life cycle.

Table 6 The Users' Statistics by Membership Life Cycle Stages

Variable	Value	Frequency Count	Percent of Total Frequency
Membership life cycle	L	774	41.7251
	I	640	34.5013
	S	441	23.7736

**Figure 4 The Users' Statistics by Membership Life Cycle (Initial/Short-term/Long-term)**

Model results

We select a 2-year study period that includes users who issued their first post between January 1, 2013, and December 31, 2014. We identify variables from two different perspectives: the goal of a user

initiates a post (initial post), and the actual support they can actually get from the community (reply post). To understand the users' goals of posting based on the content analysis, we believe the initial post in each thread will more clearly indicate the users' purposes or goals than the reply posts since most reply posts don't initiate a topic but follow a topic. The reply posts can imply the users' interests and the way they like to participate in a discussion, but they are hardly purpose-oriented. Therefore, for each thread, we investigate the initial post and categorize them into information seeking, emotional seeking, and non-support seeking posts. To examine the social support that the users can obtain from their posting, we investigate all the replies in the thread and categorize them into informational support, emotional support, non-support, and self-interaction (The user who initials the post replies the thread in order to communicate with other members who also replies to the post) posts.

We use the percentage of informational support or emotional support of a user as the measurement of how much each type of support a user received from the participation. However, the measurement is biased without considering the actual count of the support posts. For example, if a user initiated an information seeking post that was looking for information about how to use a device for self-care. There was only one user replied the post and provided related information. And this was the only post this user had posted and the only support he/she received. As such, the measurement of support received from this post is 100 percent. In another case, a user initiated an information seeking post as well, and there were 12 replies to the post, 6 of which provided related information, and other replies may include emotional support, or self-replies, or other replies that are non-support posts. It is more likely the user of this post can get more informational support. However, based on our original measurement, the support received from this post is only 50 percent (6 divided by 12). To make the measurement more reasonable, we use adjusted informational support and emotional support. The average replies of each post in the online health community Tudiabetes.org as we mentioned earlier. As such, we defined a function to

calculate the received support.
$$f(x) = \begin{cases} x/6, & \varphi(x) \leq 6 \\ x, & \varphi(x) > 6 \end{cases}$$
, where x is the percentage of a given type

of support received by a user, and $\varphi(x)$ is the count of reply post of the user's initial post. The following table shows the descriptive statistics for the variables of the research model.

Table 7 Descriptive Statistics for Variables

Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
Stay	143	0.34266	0.47627	49.00000	0	1.00000
Info_Seeking	143	0.66434	0.59273	95.00000	0	3.00000
Emot_Seeking	143	0.37762	0.65868	54.00000	0	5.00000
Ave_support	143	6.82296	7.09479	975.68333	0	43.00000
InfoSpt	143	0.39508	0.33555	56.49683	0	1.00000
EmotSpt	143	0.23536	0.29602	33.65605	0	1.00000
Adj_InfoSpt	143	0.18865	0.24913	26.97726	0	1.00000
Adj_EmotSpt	143	0.12374	0.21482	17.69545	0	0.83333
Self_interaction	143	1.53536	0.60960	219.55715	0.18124	2.29258
Match_Info	143	0.36588	0.35380	52.32066	0	1.00000
Match_Emot	143	0.19275	0.30902	27.56372	0	1.00000
Adj_InfoMatch	143	0.17486	0.25130	25.00529	0	1.00000
Adj_EmotMatch	143	0.07851	0.15880	11.22679	0	0.69444
Adj_Match	143	0.25337	0.26980	36.23208	0	1.00000

Analysis of variance (ANOVA) is a collection of statistical techniques used to analyze the potential differences in a scale-level dependent variable by a nominal-level variable having 2 or more categories. In order to understand, how each variable impact on the two groups of users (short-term survivors vs. long term survivors), we perform the ANOVA analysis to each variable. The ANOVA analysis result is as follows.

Table 8 Results of ANOVA Analysis

Variables	DF	R-square	Coeff Var	Root MSE	Mean	ANOVA SS	F	Pr>F
Info_Seeking	1	0.262871	76.87290	0.510694	0.6643	13.1141	50.28	<.0001
Emot_Seeking	1	0.278214	148.7157	0.561584	0.3776	17.1403	54.35	<.0001
InfoSpt	1	0.152423	78.46849	0.310015	0.395083	2.43701	25.36	<.0001
EmotSpt	1	0.346549	102.0309	0.240137	0.235357	4.31208	74.78	<.0001
Adj_InfoSpt	1	0.079261	127.1631	0.239896	0.188652	0.69853	12.14	0.0007
Adj_EmotSpt	1	0.096541	165.5922	0.204911	0.123744	0.63263	15.07	0.0002
Self_interaction	1	0.037424	39.09178	0.600201	1.535365	1.97481	5.48	0.0206
Adj_InfoMatch	1	0.076939	138.5638	0.242296	0.174862	0.68996	11.75	0.0008
Adj_EmotMatch	1	0.109186	191.5835	0.150410	0.078509	0.39097	17.28	<.0001
Adj_Match	1	0.004080	106.6410	0.270198	0.253371	0.04217	0.58	0.4485

Correlation analysis is a method of statistical evaluation used to study the strength of a relationship between two variables. We use correlation analysis to investigate how the different type of initial goals and supports connect with the users stay length differently. The following table shows the correlation results.

Table 9 Results of Correlation Analysis

Pearson Correlation Coefficients, N = 143										
Prob > r under H0: Rho=0										
	Info_See king	Emot_See king	InfoSpt	EmotSpt	Adj_InfoS pt	Adj_Emo tSpt	Self_inte raction	Adj_Info Match	Adj_Em otMatch	Adj_Mat ch
Stay	-0.51271	0.52746	-0.39041	0.58868	-0.28153	0.31071	0.19345	-0.27738	0.33043	-0.06387
	<.0001	<.0001	<.0001	<.0001	0.0007	0.0002	0.0206	0.0008	<.0001	0.4485

Findings and Discussion

It is remarkable to find that all the factors we identified have a strong correlation with the member's long-term stage survival. The ANOVA analysis result shows that information seeking ($F=50.28$, $p<.0001$) and emotional seeking ($F=54.35$, $p<.0001$) are significantly different between the users who survives to long term and who doesn't. The correlation analysis result shows a negative relationship between information seeking and long-term survival, and a positive relationship between emotional seeking and long-term survival. They are both significant at the level of $p<.0001$. As such, Hypothesis 1 is supported.

The results suggest that the users whose initial goal of participating in the online health community is information seeking most likely lose interest in continuance participation in the long term. This is slightly different from previous studies on online communities which believe that task-oriented activity should have a positive relationship with user acceptance. We believe this is reasonable for the following reasons. First, previous studies verified that perceived usefulness (M. K. Lee et al., 2005) is positively related to users' behavior intention. In conjunction with this, we argue that the perceived usefulness has a strong impact on users' initial intention of acceptance, yet has a very weak impact on users'

continuance participation in the long term. As many other studies proposed (Bhattacharjee, 2001b; Jin et al., 2010), if the users' expectation has been satisfied, they will lose motivation to continue. Secondly, if users get expected answers from replies to information seeking posts, they may likely come back to ask other questions. However, how many questions will they have? What happens when users have asked all their questions? On the other hand, if the users' goal focuses on asking questions and finding solutions, it would be easier and faster to search for relevant questions. One study (Nonnecke, Preece, & Andrews, 2004) showed that information seeking users usually read but seldom post. Nonnecke et al. (2004) posited that the information seeking goal can be achieved in the form of easily searched and browsable archives and other online information resources such as FAQs. Therefore, information seeking can be an initial motivation to join an online health community, but it is not a lasting driver. Our results are in accordance with the previous study. X. Wang et al. (2014) conducted a case study using an OHC among breast cancer survivors to examine how different types of social support the users provided and received can affect their engagement in the OHC. They found that users who started with a lot of information seeking posts may not get engaged in the long run. In the OHC, the informational support seekers could be very active at first, yet, have a higher chance of keeping silence or even leaving the OHCs after they get the information they want from the community (Shang & Liu, 2015; Y.-C. Wang et al., 2012).

Those looking for emotional support are most likely to continue in the online health community. Users who are motivated by utilitarian value participate in the online community for the sake of informative benefits. Users who are hedonically motivated typically enjoy participating in online communities for the sake of participation itself (Cotte et al., 2006). The users who like to share personal experiences usually feel a sense of connection and belonging with other community members. Commitment is a psychological bond that characterizes an individual's relationship with an organization (Wykes, 1998). P. J. Bateman, Gray, and Butler (2011) adapted commitment theory in an online

community setting, and believe that the affective commitment creates the bond between a member and a particular community because of the member's strong emotional attachment to that community. With the generation of this bond, members are more willing to share personal experiences and feel happy to stay in the community to support each other.

Hypothesis 2 investigates the impact of receiving informational support or emotional support on the users' long-term survival. This hypothesis is confirmed by the correlation analysis result that shows a significant negative relationship between receiving informational support and long term survival and a significant positive relationship between receiving emotional support and long term survival at $p < .0001$. The ANOVA analysis result finds the receiving informational support has an $F = 25.36$, at $p < .0001$, and the adjusted informational support has an $F = 12.14$, at $p = 0.0007$. This means there is a significant difference of users' survival time between the group of users who receive informational support and the group of users who didn't. Interestingly, although receiving informational support has a positive relationship with members' short-term survival, it has a negative relationship with members' long-term survival. Studies suggest that information available in online health community for chronic diseases such as cancer is an important factor that attracts users to participate in the group (Helgeson, Cohen, Schulz, & Yasko, 2001). However, the study (Helgeson et al., 2001) investigated the effect of 8-week support group interventions with a 3-year follow-up on the quality of life of women with early stage breast cancer, and found that people who have a more controllable illness or a less severe illness might benefit from a problem-focused discussion on providing information and enhancing control, whereas people who have a less controllable illness might benefit from an emotion-focused discussion on accommodating to the disease. Diabetes is a chronic disease that no cure has been found currently. Patients have to live and cope with the disease all their lives long. Members in the diabetes online

community, especially those who have been diagnosed for a long time, would focus more on the psychological comfort.

On the other hand, the receiving emotional support has an $F=74.78$, at $p < .0001$ and the adjusted informational support has an $F=15.07$, at $p=0.0002$ in the ANOVA analysis, indicating that long-term survivors are motivated by the emotional support they have received from the online health community and more likely to stay active in the community. The reasons for these members to stay longer can be different. They can be the emotional attachment that is built during the participation (e.g. The users may like to talk to someone in the community), or the feeling of belongings and obligation (e.g. The users may want to help others in the community since they have received support from the community), or the beliefs that the community will continue providing them the support they needed (e.g. The users may want to know how do others cope with different situations). The emotional support can help the members release stress and eliminate negative feelings, and thereby, establish a positive feeling towards the community and other community members.

Hypothesis 3 studied the effect of whether the received support matches users' initial goal. Since the exchange of informational and emotional support dominates discussion in online health communities, studies (Rodgers & Chen, 2005) have been focused on separating and comparing these two type of support. However, few of them showed interesting in how the users would be satisfied with their received informational or emotional support. Is receiving informational or emotional support itself enough for meeting users' satisfaction in an online health community? Or in another word, would the matching of support type will increase the users' satisfaction and make them stay longer in the online health community? The ANOVA analysis result is very interesting. For each type of support, whether it matches the support that is sought is significantly correlated with the users' long-term survival. However,

when we combine the two types of support together, the result is not significant. As such, Hypothesis 3 is not supported. This is interesting, but not surprising. A user can join an online health community for multiple purposes, not only for informational or emotional support. When coding the data, we exclusively categorize a single post into information seeking/support or emotional seeking/support. However, each user can have one or more than one post. To understand the users' purposes and behavior, we use the ratio to calculate the different type of support they actually received. As such, when adding the two types of seeking-support data together, it is unknown how the two types influence each other. Secondly, the data from diabetes.org shows that under each thread, most of the replies are related to the question that the initial post in the thread asked. Very low rate off-topic replies in each thread. This probably because there is an instant chatting room, where users can send messages to each other when they come up with some thought while they are online. In the meanwhile, since this is a moderated community, the unrelated posts such as an advertisement or inappropriate posts might have removed from the community.

A study (Reynolds & Perrin, 2004) based on 79 women with breast cancer on the mismatch between the support that is wanted and the support that is received, found that getting the support that one did not want was negatively related to psychosocial functioning. However, other scholars found different results. For instance, a series of studies conducted by Cutrona and colleagues (Cutrona, 1990; Cutrona, Shaffer, Wesner, & Gardner, 2007; Cutrona & Suhr, 1992) found a mixed result. These studies examined support matching on perceptions of partner sensitivity and marital satisfaction by specified emotional disclosure leading to emotional support and advice/information requests leading to informational support. The results showed that partner's sensitivity was higher when participants get matched support type – emotional support when they expressed their emotions. Interestingly, no significant influence had been found when participants made information requests whether the support is matching or mismatching the

request. Another study by Wolff, Schmiedek, Brose, and Lindenberg (2013) studied the relationship between needed and gotten emotional support on complaints about health and experience of negative effect among older and younger people, and also find a mixed results. The finding suggested that the older people reported less negative effect when they got more emotional support. However, younger people showed a nonlinear relationship between the negative affect reported and the emotional support they have gotten. They tend to have more complaints and more negative affect both when they received too little and too much emotional support that matches their needs. Similarly, another study on support matching on online health forum (Smithson et al., 2011) found receiving emotional support, in general, will help users on self-harming, yet no evidence that supports matching was beneficial in the case for asking for and receiving advice. These studies findings are consistent with our findings. Overall, there is no significant relationship between the support matching and users survival time. The support matching itself is important, however, it might be subject to other complex factors such as variations in populations, the operationalization of matching, support types, as well as outcomes measurements (Vlahovic, Wang, Kraut, & Levine, 2014).

Hypothesis 4 investigates whether the ratio of user's self-interaction in the reply post would impact the user's long-term survival. Self-interaction is measured by how many percentages of the reply posts are from the user who initiates the thread. It shows how much the user cares about the post and others' replies. Hypothesis 4 emphasizes an appropriate engagement rate of the users' self-interaction. The way of the user communicates with others will affect how much information he/she can get from others. It is obviously showing careless if the user who initiates the first post of thread never comes back to check the answers or never interacts with other users who provide answers and discusses the problem in the thread. However, too high percentage replies are made by the owner of the thread also indicates that the post might have difficulties to get enough attention by other users or attractive enough user to answer

the question, even though the owner has tried to keep the post active. Therefore, the impact of self-interaction on users' received support should be a bell curve-like relationship. We use normal distribution density function to represent the curve of members' self-interaction, and then find it has a positive relationship with users' long-term survival. The ANOVA result is $F=5.48$, at $p=0.0206$. This confirms our hypothesis that the way how a user interacts with others in the discussion forum will affect their decision of stay or leave the online health community.

Interaction style of discussion forums has been studied by some scholars (Huh, McDonald, Hartzler, & Pratt, 2013). One concern is the absence of nonverbal cue might occurs misunderstanding, and affect the communication quality. There have been some studies (Becker-Beck, Wintermantel, & Borg, 2005) that compared the communication styles in terms of face-to-face communication (FTF) and computer-mediated communication (CMC). CMC is known to have low interaction rate and take longer to complete tasks comparing with FTF (Becker-Beck et al., 2005). A study of comparing text-based CMC with FTF communication by (Reid, Malinek, Stott, & Evans, 1996) found that the number of time-critical social-emotional messages transmitted in task-oriented settings should be comparatively lower in CMC groups than in FTF groups due to the costs for sending a message are higher in CMC than in FTF. However, getting social-emotional support is one of the most important reasons that users come to the online health community. It makes sense that the users who make the effort on ameliorating interaction and improving the communication quality will receive better support.

Table 10 Summary of Findings of Study I

Hypothesis	Description	Result
H1-1	User's initial goal likely leads to long-term survival when he/she seeks peers' experience (emotional support seeking), whereas it likely leads to short-term	Supported

	survival when the user seeks peers' information (information seeking).	
H1-2	User's received support type likely leads to long-term survival when he/she receives emotional support, whereas it likely leads to short-term survival when the user receives informational support.	Supported
H1-3	A user is more likely survived to the long-term stage than the short-term stage when the type of support he/she received matches his/her initial goal.	No
H1-4	A user is more likely survived to the long-term stage than the short-term stage if he/she appropriately engages (self-interaction) in the discussion of the posts he/she has initiated.	Supported

The prediction of users short-term vs. long-term survival

In the former section, we find that the information seeking, emotional seeking, informational support, emotional support, information seeking-support matching, emotional seeking-support matching, and users' self-interaction rate and the average support a user received, are related to users' long-term survival. In this section, we conduct a regression model for predicting users' long-term survival based on their initial stage activities. The following table shows the Logistic regression result.

Table 11 Logistic Regression Output for Study I

Independent Variables	Analysis of Maximum Likelihood Estimates				Odds Ratio
	Estimate	Standard Error	Chi-Square	Pr > ChiSq	Point Estimate
Info_Seeking	-1.8081	0.7789	5.3883	0.0203	0.164
Emot_Seeking	2.5051	0.8380	8.9369	0.0028	12.245
Adj_InfoSpt	-9.5264	3.8619	6.0850	0.0136	<0.001

Adj_EmotSpt	-8.3505	3.0096	7.6985	0.0055	<0.001
Self_interaction	1.5489	0.5095	9.2424	0.0024	4.706
Ave_support	0.0664	0.0413	2.5814	0.1081	1.069
Adj_Match	8.6868	3.7249	5.4386	0.0197	>999.999

The logistic model shows that we can predict users' behavior in terms of short-term survival or long-term survival by analyzing their initial stage activities. The Emotional seeking and self-interaction are significant at $p < 0.005$ level; Adjusted emotional support is significant at $p < 0.01$ level; Information seeking, adjusted informational support and adjusted seeking/support match are significant at $p < 0.05$ level. We include a control variable "average support" in the regression model. However, the result is significant at $p = 0.1081$, and the coefficient is only 0.0664. It shows a very low impact of average support on the users' long-term survival. A couple of reasons may explain this phenomenon. First, as a moderated-community, most posts on Todiabetes.org could get a reasonable amount of attention. Secondly, the difference in average support mostly based on the topic itself, but not the user, meaning each user has some posts that could get higher average support and some ones that could get lower average support. However, when calculating the average support of each user, the variable has very small impact on users' overall decision making.

It is very interesting to find that we can predict users' short-term survival vs. long-term survival based on the initial stage's activities. To understand users' behavior pattern can help the online health communities and health care providers better serve the patients. However, the users' stage length is one of the two aspects of users' continuance participation. In the online health community, not only the survival time, but also the users' activeness are the keys to the community success. As such, we conduct the second study to understand the users' activeness during their membership life cycle. We investigate

what are the factors that drive users to be active during the short-term and long-term stages, and how do the factors work differently during different stages.

STUDY II: SHORT-TERM VS. LONG-TERM ACTIVENESS

The second study is interested in users' activeness in their different stage of membership life cycle. In order to compare users' activeness in the different stage, we focus on the users that are still active in long-term stage, so that we can have the data of the users' posting activity from their initial stage, short-term stage, and long-term stage.

Theory building and hypothesis development

Users' activeness in online communities has long been interested by scholars (Crandall, Cosley, Huttenlocher, Kleinberg, & Suri, 2008; M.-C. Lee, 2010; Shang & Liu, 2015; K. Zhao et al., 2013). Theories in social psychology, organizational behavior, sociology, and economics have been deployed to study and understand users' activeness and success of the online communities. For example, social support theory (Bambina, 2007; X. Wang et al., 2014) is used to investigate users' engagement in online community, social psychology theory of social loafing and goal setting (Ling et al., 2005) is used to attract users to contribute to the online community, group identity and interpersonal bonds (Ren, Kraut, & Kiesler, 2007; Sassenberg, 2002) are used to develop users attachment to the online community, and identity-based view (Ma & Agarwal, 2007) is used to suggest the impact of reputation on users participation in the online community.

Expectation-confirmation theory (ECT) is widely used in the consumer behavior literature to study consumer satisfaction, post-purchase behavior, and service marketing (E. W. Anderson & Sullivan, 1993; Dabholkar, Shepherd, & Thorpe, 2000). Since IS user' continuance decision is similar to consumers' repurchase decision, ECT model is frequently adapted by IS scholar in study technology

adoption and IS continuance (Bhattacharjee, 2001b; Hossain & Quaddus, 2012). ECT holds the idea that consumers' satisfaction with the user of a product or service is the primary determinant of their intention to repurchase the product or continue service (Oliver & Linda, 1981). The user's decision of continuance using and whether to stay active in online health community is a similar process. Satisfaction is formed by the expectation and confirmation process from previous experience. In online health community, the experience of initial stage participation can provide valuable clues in understanding short-term stage activeness. It is the same that short-term stage participation will have an impact on long-term stage activeness.

Based on previous studies on motivating members' activity in the online community, Ren and Kraut (2011) summarized the benefits that members can receive from participating in the online community. The users in online health community would make the decision of staying active or not at any time of their membership life cycle. The users are attracted to an online community when they expect the benefits of involvement outweigh the costs (Butler et al., 2014). As rational individuals, the users would make the decision based on their previous experience of benefits and cost in pursuing their objectives.

The current stage benefits of participation clue to post-stage activeness

Butler (2001)) proposed that participation in an online community can be defined as the actions that members take to be exposed to the communication activities, including reading messages, posting messages, as well as replying messages. The utility-like logic underpinning theory suggests that each member would assess their expected benefits and costs to choose their behavior strategies to maximize their interests. As such, we assume that a member will stay active in the online health community in

terms of logging into their account to read, to post or to reply messages when expected benefit from participation exceeds expected cost.

Ridings and Gefen (2004)) identified four types of motivations that drive users to join the online community: information exchange, social support exchange, friendship, and recreation. Based on the motivation types, Ren and Kraut (2011)) classified the benefits of using online health community into three categories: benefit from informational support, benefit from social attachment, and benefit from recognition and reputation. Following this light, we also include the above mentioned three types of benefits. What is more, we also include the benefit from emotional support since emotional support is a very important characteristic of the online health community, and it is part of the benefit from social support exchange (Shumaker & Brownell, 1984). Particularly, informational and emotional support have been found as the most frequently offered types of support as well as the types that are deemed most helpful by participants (Guthrie & Kunkel, 2016) in OHCs. Therefore, the member benefits of participation are summarized in the following table.

Table 12 Member Benefits of Participation

Benefits of Participation		Description
Social Support	Informational support	Members can get benefits from the informational support by reading informational posts in the OHC and getting answers to their information seeking questions from the OHC
	Emotional support	Members can get benefits from the emotional support by reading

		emotional/experience sharing posts in the OHC and getting answers to their emotional/experience seeking questions from the OHC
Social attachment		Members can get benefits from being connected with peers
Recognition and reputation		Members can get benefits from being recognized and building up their reputation in the online health community through the participation.

Benefit from social support:

Social support theory from the psychological and social science are frequently deployed to study users' motivation and behavior in the online health communities (Berkman & Glass, 2000; Frost & Massagli, 2008; Heaney & Israel, 2008). Evidence has accumulated in past few decades that the primary purpose of patients to access to online health community is getting informational support (Meric et al., 2002) and/or emotional support (Fogel, Albert, Schnabel, Ditkoff, & Neugut, 2002; Høybye, Johansen, & Tjørnhøj - Thomsen, 2005), which are the top two types of social support that users are looking for in the OHCs in literature. In our first study, we focused on the influence of social support on members survival time during the short-term vs. long-term stage. In this study, we will investigate how the received social support affects users' activeness during the short-term and long-term stages.

Informational support: Members can get access to the information and knowledge they need to manage their conditions or disease by posting their questions and waiting for the answers from other

members in the OHCs. Informational support has been the most frequently exchanged support type in online health community (Coursaris & Liu, 2009). The benefit from informational support is very straight forward. The following example is a newly diagnosed diabetes patient looking for advice on treatment choices of CGM vs. injections.

“I have recently been diagnosed with T1D and I am giving myself injections at mealtime and long lasting every 24 hrs to stabilize my BG levels. I do not plan on switching to a pump in the near future, but I am considering a CGM. I discussed this with my endo and she did not recommend using a CGM unless I was using a pump and she didn't really explain the drawbacks of a CGM + injections. Will the CGM still be worth it if I am using injections or will it be a waste of money? The thing that is so attractive to me about the CGM is that it can tell me if I'm trending low before I start to feel too bad. I play division I college soccer and a CGM would really be a life saver to me.... but would it be as affective in tandem with injections?”

There were 64 reply posts from 30 different users. The discussion focused on what are the choices the other members made, what are the factors the other members considered when they select their treatment, and what do they think about their choices, and so forth. I quoted a few sentences of some of the reply posts below.

“Due to insurance issues I wound up starting on dexcom g4 cgm for about a month or two before getting my tslim pump. I will say that the info I was able to acquire from using the cgm and MDI was invaluable in my level of control.....”(Replier#1)

“I don't use a CGM, but it's my understanding that the results are delayed by about 20 minutes from the actual blood sugar level. It was my understanding that, because of this, a CGM was more useful for spotting trends and adjusting doses than it was for detecting lows.”(Replier#2)

“I'm on MDI and I've been using the Dexcom for about three months. I think it provides incredibly valuable information to me on a constant basis. I think you're right that it would probably be very helpful for you as an athlete. I've never understood endos who think it's only beneficial with a pump.” (Replier#3)

Members provided their advice based on their different experiences with CGM and injections, and the member who starts the thread can make his/her decision based on these experiences. The information is beneficial to the member who asks the question since she/he doesn't need to try each of the treatment to compare which one is a better choice in his/her situation.

Emotional support: Members can get emotional support to help them cope with the stress of living with certain diseases and thereby, improve life quality. We use emotional support benefit in according with the motivation of social support exchange (Ridings & Gefen, 2004). Prior studies show emotional support enhance patients' satisfaction by providing regulating emotion (Earnshaw et al., 2015). The following example shows how a member received emotional support in the online health community when he/she needed someone to talk.

“Hey I'm Rebecca, And I guess I'm sort of new to talking to people about this but I need someone to relate to me. I've had diabetes for 7 years now, and I'm 20 years old. I've had

dka 4 times in that time frame. No one else in my family has type I. I've just been having a hard time lately and I feel like my friends or family understand why."

There were 11 replies from 11 different members. I quoted some sentences from the reply posts below.

"Hi Rebecca!! I'm still relatively new to this whole d thang myself... I will have 2 years under my belt come April. But I know I struggled with my relatives at first ...When I wanna scream at the top of my lungs cuz I feel overwhelmed I post and can honestly say the people here are awesome. They have great advice and are very supportive" (replier#1)

"I am here for you. I am 59 T1 and have been dealing with this for a little over a year. I do have 2 younger brothers with T1 and they are great support. Hang in there. This site has done so much to help me. Hardly a day goes by that I am not checking it out. Chin up. You can do this." (replier#2)

"Hi Rebecca(,) glad you found this place. I've been T1 for almost 18 years and I still struggle with not having anyone in my life that understands what I deal with. When I feel frustrated I talk to a friend or I come here to discuss my feelings. Just know there are people who get it and feel what you feel and you're not alone. Hang in there ;)"(replier#3)

"Hi Rebecca Welcome to our lovely site! I am glad you found us.."(replier#4)

"Hey there, sweetie. I'm a T2 for 7 years, but I have a lot of T1 friends, as well as friends who are insulin-dependent T2s. I may not understand the complexities of your daily self-

management, but I totally understand the emotional upheaval that comes and goes in waves with our common scourge....."(replier#5)

The members can relieve stress, anxiety, and other negative feelings by reading similar experiences from their peers. The encouraging and comforting posts are beneficial to members in the form of emotional support.

We have proven that the social support is the factor that affects users' survival time. In this study, we argue that social support benefit will positively affect users' activeness in their later stage. However, the impact power is differently as users move into different stages of their membership life cycle.

Information exchange and social support are the most common reason for members joining an online community (Ridings & Gefen, 2004). Expectation-Confirmation Theory (ECT) (Bhattacharjee, 2001b) suggested that users' satisfaction will lead to their intention of continued use of information technology. Especially, Bhattacharjee (2001a) conduct an empirical study to examine key drivers of consumers' intention to continue using business-to-consumer e-commerce services. It provides solid evidence that consumers' continuance intention is determined by their satisfaction with initial service use. During the initial stage, the users' primary criteria for evaluating whether they are satisfied with the utilization of the online health community are whether they could get the social support they sought. As such, the social support the user received during their initial stage should be an important indicator towards the user's short-term activeness.

However, the users who moved into short-term stage already have some positive experiences during the initial stage and desire to evolve more activities in the future discussion. The users investigate the community's value by participating with the primary purpose of deciding to stay or leave in the

initial stage, whereas getting what they want from the community in the short-term stage. The short-term stage participatory helps the users to learn knowledge and improve emotion. That is to say, the users grow with the community, and their roles may change from seekers to contributors. As such, the importance of receiving support reduces over time. Accordingly, we propose the following hypotheses:

Hypothesis 2-1a: Higher social support a user received during the initial stage is likely to lead to higher user activeness during the short-term stage.

Hypothesis 2-1b: The social support a user received during the short-term stage is likely to have little impact on users' activeness during the long-term stage.

Benefit from social attachment: The attachment theory was originally developed to study a child's tie to the mother and its disruption to separation, deprivation and bereavement (Bretherton, 1985, 1992; Cassidy & Shaver, 2002). It was then adapted by social psychology and social economic scholars to study individuals' social behavior (Pietromonaco, Uchino, & Dunkel Schetter, 2013; Tops, Koole, IJzerman, & Buisman-Pijlman, 2014). Previous studies believe that members' interpersonal bonds with other members can lead them to become committed to the community (Prentice, Miller, & Lightdale, 1994; Sassenberg, 2002). Commitment refers to the state or quality of being dedicated to a cause, activity and so forth. In organizational behavior and organizational psychology domain, commitment is the individual's psychological attachment to the organization (Mowday, Steers, & Porter, 1979). The commitment enacts an engagement or obligation that prevents employees from leaving the organizations, and has long been proven has prediction power on work variables such as turnover, organizational citizenship behavior, and job performance (Porter et al., 1974; Williams & Anderson, 1991). The widespread diffusion of online virtual communities, some studies utilized the commitment theory to understand the users' sharing and support behavior in online communities (P. Bateman, Gray,

& Butler, 2006; Kang, Lee, Lee, & Choi, 2007). Young (2013) believed that the success of an OHC “depends, in part, on an organization’s commitment to sustained organizational and financial support for dedicated community management.” To establish the users’ commitment, online healthcare communities need to possess a strong sense of community (McMillan & Chavis, 1986), in which members share an emotional connection.

In our model, we assess social attachment by investigating how members interact and connect with each other based on the discussion thread in the OHC. The social attachment in terms of users’ commitment towards the community members and the community is built over time. It is hard to build up the attachment during the first two weeks of joining the online health community. Accordingly, we propose the following hypotheses:

Hypothesis 2-2a: The users’ social attachment towards to the OHC during the initial stage is likely to have little impact on users’ activeness during the short-term stage.

Hypothesis 2-2b: Higher the users’ social attachment towards to the OHC during the short-term stage is likely to lead to higher user activeness during the long-term stage.

Benefit from recognition: Members are motivated to contribute to online health communities by the recognition and reputation which may gain through their participating behavior. Recognition “can be extremely powerful incentives so long as they are public, infrequent, credible, and culturally meaningful”(Tedjamulia, Dean, Olsen, & Albrecht, 2005). In the online community, peer recognition typically encompasses community-based inducement mechanisms that encourage the participation of members. For example, badges are used to celebrate certain achievement (stackoverflow.com), top reviewers list is used to recognize excellent reviewers (Amazon.com). Even when official recognition is

absent (Ren & Kraut, 2011), active contributors often get recognized and respected as an expert in certain topics or areas by other members.

"Recognition can be either a simple acknowledgment of a user contribution or a more elaborate response appreciating this contribution"(Jabr, Mookerjee, Tan, & Mookerjee, 2013). We used the reading count of a post as an indicator to record the acknowledgment of the user's contribution. Additionally, studies (Forman, Ghose, & Wiesenfeld, 2008; Ghose, 2009) suggest that peer feedback as one inducement approach to show users' contributions are acknowledged and appreciated by others. Others (Xiong & Liu, 2004; Zacharia, 1999) related reputation to trust building and argued that users' with higher recognition and reputation by community-based inducement mechanisms are easily trusted by other users. Velasquez, Wash, Lampe, and Bjornrud (2014) found that users are motivated by the recognition they derive from the feedback (such as voting systems) of their participation in the online community. Accordingly, we propose the following hypotheses:

Hypothesis 2-3a: Higher recognition a user gains during the initial stage is likely to lead to higher user activeness during the short-term stage.

Hypothesis 2-3b: Higher recognition a user gains during the short-term stage is likely to lead to higher user activeness during the long-term stage.

The current stage participating characteristics clue to post-stage activeness

While members can get different types of benefits from participating in the online health community, there are some other factors that may also influence the users' post-stage activeness. "While individuals all engage a community through these general processes, they differ with respect to their

initial expectations, their preference to contribute posts, and their interests”(Butler et al., 2014). The participating characteristics include activeness, topic breadth, and topic initiation.

The **activeness** refers to how many posts a user contributed in the current stage. To some extent, it shows how much the user is interested in participating in the discussion of the online health community. As we mentioned earlier, during the initial stage, users’ primary goal is to find answers to their questions or problems. A high expectation of getting answers would be the key impetus of high activeness in the initial stage, and it should also be the antecedent of the short-term activeness. The same logic applies to the short-term stage participation clue to the long-term activeness. Accordingly, we propose the following hypotheses:

Hypothesis 2-4a: Higher user activeness during the initial stage is likely to lead to higher user activeness during the short-term stage.

Hypothesis 2-4b: Higher user activeness during the short-term stage is likely to lead to higher user activeness during the long-term stage.

The **topic breadth** refers to how many different topics a user participates in during the current stage. It shows the breadth of topics of a users’ involvement within the online health community. Similar variables were used in past studies (Jabr et al., 2013) to examine user contribution level in the online community. If a user participated in a broad range of topic, most likely he/she has a high interest level towards to the community, and most likely lead to a high activeness in the post-stage. Accordingly, we propose the following hypotheses:

Hypothesis 2-5a: Higher topic breadth during the initial stage is likely to lead to higher user activeness during the short-term stage.

Hypothesis 2-5b: Higher topic breadth during the short-term stage is likely to lead to higher user activeness during the long-term stage.

The **topic initiation** refers to the amount of thread that a user initiated during current stage participation. In the online health community, there are two types of posts: the initial post and the reply post. The user who initiates a post usually has a question to ask or a story to share. Given the high percentage of information seeking posts in the online health community, higher initial post means more questions. During the initial stage, users' primary goal is to obtain the support they expected. Higher initial posts mean the user has asked more questions, and he/she would expect to get answers from the community. This is because if a user asked a question, but didn't get any answer or didn't get meaningful answers, he/she would stop asking. If a user keeps asking different questions in the online health community, most likely he/she received the requested answers from the previous experience.

However, as we mentioned earlier, users who moved into their short-term stage change their primary goal over time. The users' role changes from support seekers to support providers. As such, the topic initiation will decrease as time goes by.

Accordingly, we propose the following hypotheses:

Hypothesis 2-6a: Higher topic initiation during the initial stage is likely to lead to higher user activeness during the short-term stage.

Hypothesis 2-6b: The topic initiation during the short-term stage is likely has little impact on users' activeness during the long-term stage.

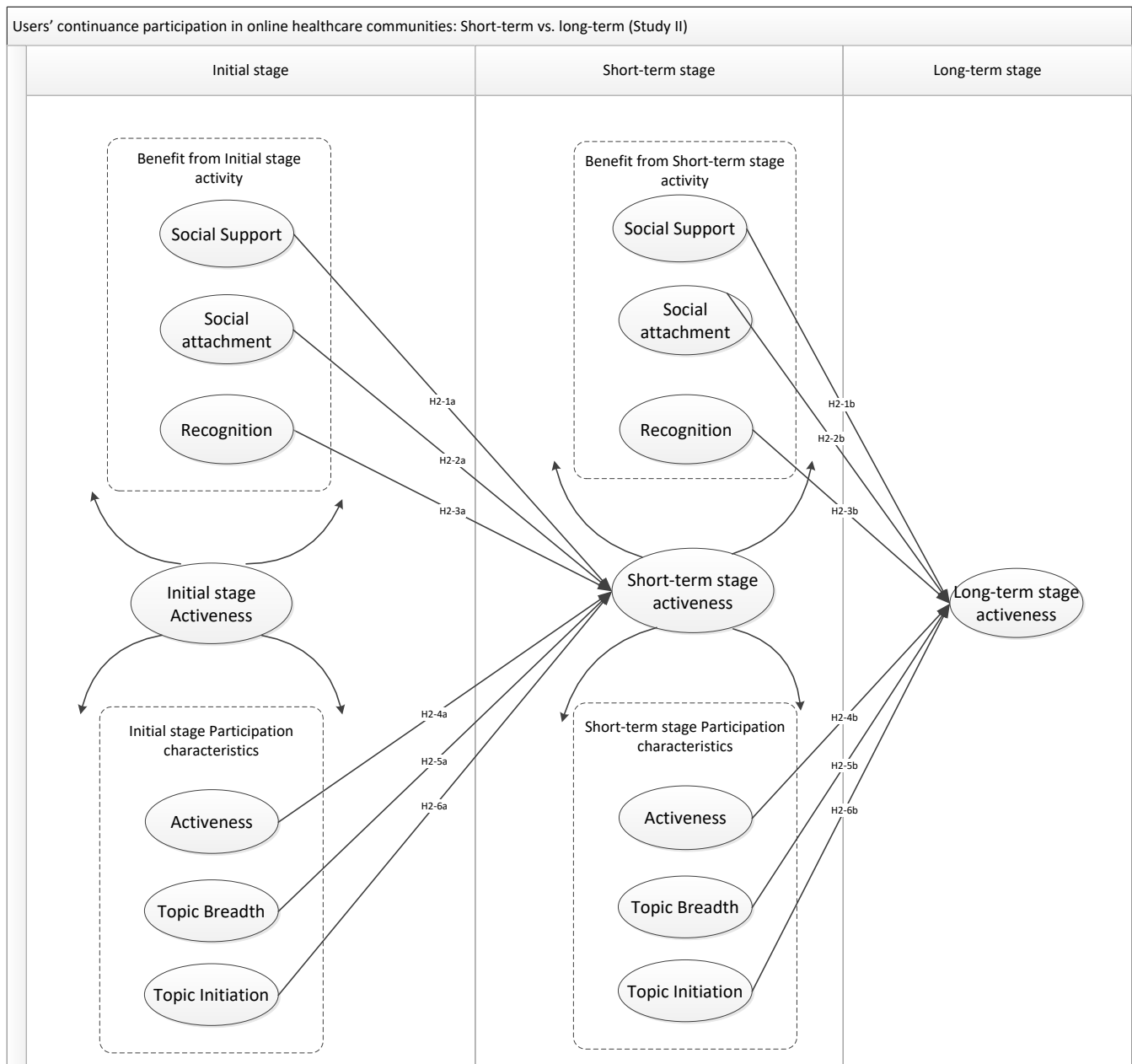


Figure 5 Research Model for Study II

Research Methodology

Model Measurements

Table 13 Model Measurements and Variable Descriptions

	Constru cts	Variable Name	Variable Description
	Short-term Stage Activeness	Short_Activeness	The number of posts contributed by a user during the short-term stage
	Long-term Stage Activeness	Long_Activeness	The number of posts contributed by a user during the long-term stage
Benefits from participation activity	Social Support	Drct_support	The number of reply posts a user received for his/her initiated posts during the current stage
	Social Attachment	Connection	The number of participants a user connected with through his thread discussion during the current stage
	Recognition	Reads	The number of “reads” that a user’s post during current stage was received by other users
		WLikes	The number of “likes” that a user’s post during the current stage was received from other users
Participating Characteristics	Activeness	Count_posts	The number of posts that a user contributed to the online health

			community during the current stage
	Topic Breath	Count_topics	The number of threads that a user participated in during the current stage
	Topic Initiation	Starter_I/S	The number of initial posts that a user contributed to the online community during the current stage (Starter_I is during initial stage; Starter_S is during short-term stage)

Data collection

To keep the consistency of this dissertation research, we use the data from the same study period in the study I for the second study: the members who created their account and posted their first post between January 1, 2013, and December 31, 2014. The dataset contains all the users' life time posts from their first post to their last post until the time point when we collected the data. The data pre-preparing process is similar to the first study.

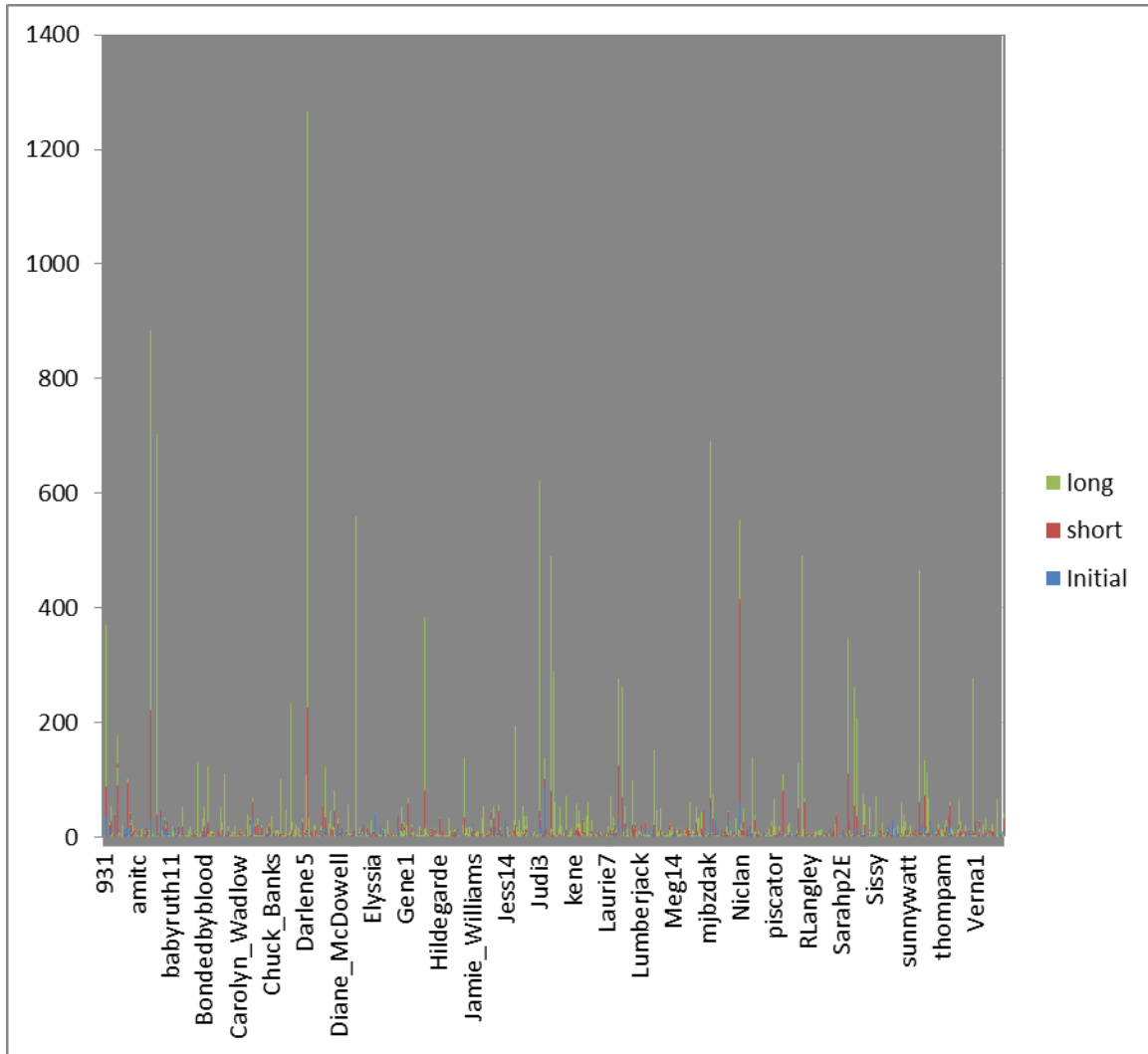


Figure 6 The Distribution of Users' Activeness by Stage

This figure graphically shows the users' activeness by stage in our sample data. The following table is the descriptive data of users' activeness.

Table 14 The Descriptive Statistics of Users' Activeness

Variable	Mean	Std Dev	Minimum	Maximum	N
----------	------	---------	---------	---------	---

Variable	Mean	Std Dev	Minimum	Maximum	N
Initial_activeness	2.3924528	4.7791740	0	86.0000000	1855
short_activeness	3.0582210	13.2975189	0	353.0000000	1855
long_activeness	7.8851752	48.2681993	0	1041.00	1855

Model results

Initial stage to short term stage

We organized the data by users and separated the data for each user by stage. In the first model, the dependent variable is the short-term activeness, which is the total post count of the short-term stage for each user. All the independent variables are from the initial stage. The descriptive statistics are shown in table 2-4.

Table 15 Descriptive Statistics of Variables for Short-term Activeness

Variable	N	Mean	Std Dev	Minimum	Maximum
Short_activeness	198	16.4747475	36.4089417	1.0000000	353.0000000
Reads	198	2.8484848	16.1228555	0	220.0000000
Wlikes	198	0.0028319	0.0201340	0	0.2000000
Connection	198	1.1010101	1.1128684	0	8.0000000

Variable	N	Mean	Std Dev	Minimum	Maximum
Drct_support	198	0.1616162	1.0345020	0	10.0000000
Count_posts	198	2.0505051	2.7809130	0	16.0000000
Count_topics	198	2.6464646	2.3664882	1.0000000	16.0000000
Starter_I	198	0.5707071	1.0088696	0	6.0000000

The results of the regression analysis are included in table 2-5. The analysis of the model indicates a good fit, with an $F=13.38$ at $P<0.0001$. The R-square value is 0.3302.

Table 16 Regression Output for Model 1

Variable	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	-1.73205	3.43248	-0.50	0.6144
Reads	0.58098	0.17601	3.30	0.0012
Wlikes	30.75034	134.34204	0.23	0.8192
Connection	-0.32175	2.67976	-0.12	0.9046
Drct_support	-4.03105	2.15575	-1.87	0.0630
Count_posts	-1.03865	1.04937	-0.99	0.3235
Count_topics	5.41698	1.15358	4.70	<.0001
Starter_I	9.22441	2.44862	3.77	0.0002

Short term stage to long term stage

In the first model, the dependent variable is the long-term activeness, which is the total post count of the long-term stage for each user. All the independent variables are from the short-term stage. The descriptive statistics are shown in table 2-6.

Table 17 Descriptive Statistics of Variables for Long-term Activeness

Variable	N	Mean	Std Dev	Minimum	Maximum
Long_activeness	198	50.1767677	132.7327151	1.0000000	1041.00
Reads	198	1.5555556	5.9031476	0	68.0000000
Wlikes	198	0.0220490	0.2842620	0	4.0000000
Connection	198	1.3131313	1.0724654	0	8.0000000
Drct_support	198	0.1616162	0.9738413	0	8.0000000
Count_posts	198	2.2525253	3.4957362	0	32.0000000
Count_topics	198	6.9090909	10.7727716	1.0000000	77.0000000
Starter_S	198	0.9141414	1.9479788	0	12.0000000

The results of the regression analysis are included in table 2-5. The analysis of the model indicates a good fit, with an $F=18.35$ at $P<0.001$. The R-square value is 0.4072.

Table 18 Regression Output for Model 2

Variable	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	-10.50650	12.43355	-0.85	0.3992
Reads	0.31525	1.36548	0.23	0.8177
Wlikes	-8.97821	26.72565	-0.34	0.7373
Connection	17.14598	8.06958	2.12	0.0349
Drcr_support	3.89513	8.30828	0.47	0.6397
Count_posts	-7.10280	2.55621	-2.78	0.0060
Count_topics	7.79063	0.90828	8.58	<.0001
Starter_S	-0.10070	5.09511	-0.02	0.9843

Findings and Discussion

The purpose of this study is to identify the factors that affect users' short-term and long-term activeness from users' earlier stage participation and to understand why the impact of these factors is different during the different stages. The results are very interesting and promising. As we expected, the benefits and participating characteristics have quite different results on users' post-stage activeness. The following table compares the regression output.

Table 19 Comparison of Regression Output for Model 1 and Model 2

Variables	Initial to Short-term Activeness		Short-term to Long-term Activeness	
	Coefficient	Significant	Coefficient	Significant

Drct_support	-4.05552	0.0628	3.89513	0.6397
Connection	-0.70257	0.7965	17.14598	0.0349
Reads	0.57245	0.0015	0.31525	0.8177
Wlikes	35.04554	0.7956	-8.97821	0.7373
Count_posts	-0.98047	0.3546	-7.10280	0.0060
Count_topics	5.44394	<.0001	7.79063	<.0001
Starter_I/S	9.44961	0.0002	-0.10070	0.9843

The impact of social support on users' post-stage activeness from initial stage participation to short-term activeness is weakly supported at a $p=0.0628$ level. However, it is not significant from short-term stage participation to long-term activeness, which means the amount of social support a user received in the short-term stage has no significant impact on the users' long-term activeness. Surprisingly, the relationship between the receiving support during the initial stage and the users' activeness during the short-term stage is negative. As such, H2-1b is supported, yet H2-1a is not. Receiving social support is the initial expectation of most of the members when they join the online health community. During the initial stage, users access the community's performance (e.g. the knowledge base the community can provide to me, the peers that I can connect with through the community) in comparing with their expectation, and determine the extent to which their expectation is confirmed. Based on their initial expectation and confirmation level, the users form a satisfaction. However, the negative relationship implies that users are less active in the short-term stage if they received what they want in the initial stage. It is possible that because of the satisfaction of support received during the initial stage, the user would have fewer questions to ask in the short-term stage. Since we want to compare how do the affecting factors work differently during the different stages, users in our dataset are the long-term users, who have posts in all of the three stages. The parameters are

not used to investigate users' stay time. All the users in this dataset are survived into the long-term stage. As such, a negative relationship doesn't mean users will stop coming but just be less active. Receiving support is the reason that the user chooses to stay in the online community, but probably not a driver makes a user contribute more posts.

However, during the short-term stage, the users' expectation may start to change. They have learned basic information, knowledge, and experience. The primary goal can be to build up the feeling of belonging to and identifying with the community, to influence and/or be influenced by other peers of the community, or to share an emotional connection, according to McMillan and Chavis (1986). This process of changing participation expectation and patterns is considered as the commitment building process. Literature (Chuang, Chiu, He, & Chu, 2015; Wu & Sukoco, 2010) suggests that users' desire of contributing to the community is the impetus of users' activeness. Thus, the commitment arouses the OHC members' desire of repaying the community by providing more support to others. One of the manifestations of the commitment to the community would be dramatically increased in the number of answer posts and decreased in the number of question-asking posts. As users' primary focus shifts from what they can get to what they can offer, how much support the user can receive from the community is not important anymore. This is consistent with our result that the impact of social support received during short-term stage participation is not significant to users' activeness during the long-term stage.

Hypothesis 2-2a and 2-2b investigated how social attachment influences users' post-stage activeness. The regression results show that the initial stage social attachment has no significant impact on user short-term activeness. However, the short-term stage social attachment has a significant impact on user long-term activeness at $P=0.0349$. Hypothesis 2-2a and 2-2b are supported. Social attachment refers to users' emotional connection to others. It is identified by the study (Ledbetter, 2009) as a

motivation that fosters online communication. A study conducted by (Wright, 1999) investigated the impact of participation in online support groups and found that the larger is the social connection network size, the higher satisfaction with the usage of online support groups. However, a large size of connection needs time to build. The initial stage is the first weeks of a users' membership lifecycle. The time limitation makes it hard to establish enough connection for a good size of social network. It is reasonable that the social attachment towards to the OHC during the initial stage has less impact on users' short-term activeness. In contrast, the social attachment towards to the OHC during the short-term stage act as a key factor that is affecting users' long-term activeness. As we discussed earlier, studies believe social attachment is a powerful driver that helps user commit to the OHC. The commitment may be developed when users have pleasant experiences during their short-term participation and will lead to long-term activeness. Specifically, various researchers recognizing attitude as a direct determinant of reasons for acting (Fazio, 1995; Tsai & Bagozzi, 2014), believes that the affective or emotional attachment to the community will increase the intention of contributing to the community. On the contrary, if the users have no affective emotion or attachment to the community, the need or desire of getting answers would keep users stay active during the short-term stage, yet can hardly sustain the users to stay active in the long-term stage. To maintain a successful long-term participation, users need to enjoy the activity and build up affection to the community (Lin, 2007). As such, the emotional attachment to the community would be an essential force to affect users' activeness (Dholakia, Bagozzi, & Pearo, 2004; Jin et al., 2010) in the long-term stage.

Hypothesis 2-3a and 2-3b studied whether the users' recognition has a positive relationship to the users' activeness during the post-stage. There are two indicators used to measure the users' recognition: post reads and likes. The post reads of the initial stage have a significant impact on users' activeness during the short-term stage at $p=0.0015$. However, the result is not significant between post reads of the

short-term stage and the users' activeness during the long-term stage. Surprisingly, the results showed no significant impact of both the post likes of initial stage and short-term stage on their corresponding post-stage users' activeness. Recognition is often compared with rewards in literature to understand motivation and performance (Kibria, Saha, & Howlader, 2016). A rich literature (Hansen, Smith, & Hansen, 2002) has identified recognition as a motivation for contributing to public goods (Szolnoki & Perc, 2010). Restivo and Van De Rijt (2012) conducted an experimental study on motivations of online peer contributor and found that informal rewards such as recognition significantly impact on the individual effort. Post reads show the acknowledgment of the users' contribution, is usually considered as informal recognition. No literature shows that recognition as a driver is sensitive to time or user stage. As such, it is not clear why post likes are not significant in predicting users' activeness during the long-term stage. One possible reason could be: during the initial stage, users' posts are mostly answer-seeking posts (initial posts). It is very important to have high readings so that they would get enough answers. However, during the short-term stage participation, active users have more reply posts. The reply posts don't need to be read by as many people as the answer-seeking posts need to be. Therefore, the post reads have little impact in the short-term stage.

We used the post likes as the second indicator of recognition. The post likes showed no impact on the post-stage users' activeness based on initial stage and short-term stage participation. The reason could be the voting system itself. The website Tudiabetes.org, from which we collect our data, only has the function of voting likes for the initial posts. However, the reply posts are 6 times more than initial posts on the website, and the useful information and emotional support are from the reply posts. Some members may want to vote "like" to a reply post, but since there is nowhere to do that, they may vote for the initial post instead or give up on voting that post. As such the reference value of the post like is to be

open to question. Although we tried to assign a weight to the reply posts to share the percentage of like rating from the initial post, the result is still not significant.

Hypothesis 2-4a and 2-4b investigate the relationship between users' current stage activeness and post-stage activeness. Results show no significant relationship from the initial stage to short-term stage activeness, whereas a significant relationship ($p=0.0060$) from short-term stage to long-term stage. However, the coefficient shows a negative relationship between short-term activeness and long-term activeness. As such, Hypothesis 2-4a and 2-4b were denied. These hypotheses are based on the ECT theory that satisfaction of current stage participation will lead to post-stage activeness, but dependent on an assumption that higher current stage activeness means higher satisfaction. However, it is not necessarily the case. A user could have a high volume of posts in the current stage, but stop participating post-stage, because he/she doesn't get the expected answer, or because he/she only need to get answers for a few questions. The user's decision of staying active does not simply depend on the earlier stage activeness.

Hypothesis 2-5a and 2-5b investigate the impact of the topic breadth in the current stage on users' post-stage activeness. Results show it is significant at $p<0.0001$ during both short-term and long-term stage. As such, Hypothesis 2-5a and 2-5b are supported. Study (Ren & Kraut, 2011) found that members received more informational benefit when they get access to broad topics than narrow topics. Although support seeking is the primary goal during the initial stage participation, we argue that during the short-term stage, a user may answer a broad range of topics. As we discussed earlier, active users who are building or has built their attachment and commitment towards the OHC tend to shift from support seekers to support providers. This group of the user is most likely to have a high activeness during the long-term stage.

Hypothesis 2-6a and 2-6b investigate the impact of the topic initiation in the current stage on users' post-stage activeness. Results show a significant impact of the topic initiation during initial stage on users' activeness during the short-term stage, whereas no significant impact on the topic initiation during the short-term stage on the long-term stage. As such, Hypothesis 2-6a and 2-6b are supported. As we mentioned, because of support seeking behavior, the topic initiation in the initial stage is important and has a high influence to short-term stage activeness. Yet, it has low influence from short-term stage participation to long-term stage activeness.

Table 20 Summary of Findings of Study II

Hypothesis	Description	Result
Hypothesis 2-1a:	Higher social support a user received during the initial stage is likely to lead to higher user activeness during the short-term stage.	No
Hypothesis 2-1b:	The social support a user received during the short-term stage is likely to have little impact on users' activeness during the long-term stage.	Supported
Hypothesis 2-2a:	The users' social attachment towards to the OHC during the initial stage is likely to have little impact on users' activeness during the short-term stage.	Supported
Hypothesis 2-2b:	Higher the users' social attachment towards to the OHC during the short-term stage is likely to lead to higher user activeness during the long-term stage.	Supported
Hypothesis 2-3a:	Higher recognition a user gains during the initial stage is likely to lead to higher user activeness during the short-term stage.	Supported
Hypothesis 2-3b:	Higher recognition a user gains during the short-term stage is likely to lead to higher user activeness during the long-term stage.	No
Hypothesis	Higher user activeness during the initial stage is likely to lead to	No

2-4a:	higher user activeness during the short-term stage.	
Hypothesis 2-4b:	Higher user activeness during the short-term stage is likely to lead to higher user activeness during the long-term stage.	No
Hypothesis 2-5a:	Higher topic breadth during the initial stage is likely to lead to higher user activeness during the short-term stage.	Supported
Hypothesis 2-5b:	Higher topic breath during the short-term stage is likely to lead to higher user activeness during the long-term stage.	Supported
Hypothesis 2-6a:	Higher topic initiation during the initial stage is likely to lead to higher user activeness during the short-term stage.	Supported
Hypothesis 2-6b:	The topic initiation during the short-term stage is likely to have little impact on users' activeness during the long-term stage.	Supported

CHAPTER 5

CONCLUSION

Conclusion

The OHCs are an important platform for chronic disease patients to educate themselves and help each other for self-care practices. This research studies users' continuance participation behavior and examines factors that affect users' survival time and activeness in comparing short-term vs. long-term. We find that some factors have a higher impact on short-term activeness while others have a higher impact on long-term activeness.

The impact of this research can be seen in three perspectives. For the online healthcare community owner or manager, it helps them understand the factors that affect users' continuance participation in the different period of their membership life cycle. For example, studies suggested that active members post more emotional support as compared to the less active members (Biyani et al., 2014). As such, the manager may initiate some activities to encourage members to express or share their emotional need. It can better motivate the users to maintain a high level of the activity in the online healthcare community, and therefore helps the community to be successful.

For patients, they can benefit from participating in the OHCs in terms of receiving useful information and knowledge as well as relief of mental stress. Additionally, sharing experiences can help normalize and legitimate experiences, alleviate a sense of isolation, and increase feelings of understanding, validation, and sense of belonging (Guthrie & Kunkel, 2016). Our research can help patients better understand what kinds of support are more helpful in different stages, and what kinds of

questions would be more attractive to which type of members, also how to interact with other members in the thread to get more information and support.

For the healthcare providers, a good understanding of users' seeking and supporting behavior in OHC can help them to establish a channel to disseminate healthcare information, enhance communication and interactions with patients and maybe even facilitate a way for healthcare education.

Limitations

In the OHC, members can also get benefits from recreation. In other words, members may enjoy reading posts and sharing personal experience in the community. The participation itself can provide the members' satisfaction or enjoyment. For example, some posts discuss non-health-related topics, including greetings, chat, and other contents with no purposive value but to build a friendly environment in the OHC. Users' purpose for posting this type of posts usually has nothing to do with obtaining information and knowledge to manage their illness or expressing anxiety to get emotional support, but just getting to know each other or provide a friendly atmosphere. However, it may be hard to measurement the recreation benefits, since it is a feeling of enjoying the participation. This type of indicator can usually be measured by a survey. In this study, we attempt to understand users' participation behavior by analyzing their posts and related activity data without asking the users opinion or intention. As such, we didn't investigate the recreation benefit in our model.

REFERENCE

- Al-Debei, M. M., Al-Lozi, E., & Papazafeiropoulou, A. (2013). Why people keep coming back to Facebook: Explaining and predicting continuance participation from an extended theory of planned behaviour perspective. *Decision support systems*, 55(1), 43-54.
- Alfi, M., & Talbot, P. (2013). Health-related effects reported by electronic cigarette users in online forums. *Journal of Medical Internet Research*, 15(4).
- AmericanDiabetesAssociation. (2009). Standards of medical care in diabetes—2009. *Diabetes care*, 32(Suppl 1), S13.
- Anderson, E. W., & Sullivan, M. W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing science*, 12(2), 125-143.
- Anderson, N. B. (1998). Levels of analysis in health science: A framework for integrating sociobehavioral and biomedical research. *Annals of the New York Academy of Sciences*, 840(1), 563-576.
- Andrews, D. C. (2002). Audience-specific online community design. *Communications of the ACM*, 45(4), 64-68.
- Armstrong, A., & Hagel, J. (2000). The real value of online communities. *Knowledge and communities*, 85-95.
- Ashforth, B. E., Saks, A. M., & Lee, R. T. (1998). Socialization and newcomer adjustment: The role of organizational context. *Human relations*, 51(7), 897-926.
- Bambina, A. (2007). *Online social support: the interplay of social networks and computer-mediated communication*: Cambria press.
- Bandura, A. (1995). *Self-efficacy in changing societies*: Cambridge University Press.
- Barratt, M. J., & Lenton, S. (2010). Beyond recruitment? Participatory online research with people who use drugs. *International Journal of Internet Research Ethics*, 3(1), 69-86.
- Bateman, P., Gray, P., & Butler, B. (2006). Community commitment: How affect, obligation, and necessity drive online behaviors. *ICIS 2006 Proceedings*, 63.
- Bateman, P. J., Gray, P. H., & Butler, B. S. (2011). Research Note-The Impact of Community Commitment on Participation in Online Communities. *Information Systems Research*, 22(4), 841-854.
- Baum, A. (1990). Stress, intrusive imagery, and chronic distress. *Health psychology*, 9(6), 653.
- Beach, L. R., & Mitchell, T. R. (1990). Image theory-a behavioral-theory of decision-making in organizations. *Research in organizational behavior*, 12, 1-41.
- Becker-Beck, U., Wintermantel, M., & Borg, A. (2005). Principles of regulating interaction in teams practicing face-to-face communication versus teams practicing computer-mediated communication. *Small Group Research*, 36(4), 499-536.
- Berkman, L. F., & Glass, T. (2000). Social integration, social networks, social support, and health. *Social epidemiology*, 1, 137-173.
- Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social science & medicine*, 51(6), 843-857.
- Bhattacharjee, A. (2001a). An empirical analysis of the antecedents of electronic commerce service continuance. *Decision support systems*, 32(2), 201-214.
- Bhattacharjee, A. (2001b). Understanding information systems continuance: an expectation-confirmation model. *Mis Quarterly*, 351-370.
- Biyani, P., Caragea, C., Mitra, P., & Yen, J. (2014). *Identifying Emotional and Informational Support in Online Health Communities*. Paper presented at the COLING.
- Bond, G. E., Burr, R., Wolf, F. M., Price, M., McCurry, S. M., & Teri, L. (2006). Preliminary findings of the effects of comorbidities on a web-based intervention on self-reported blood sugar readings among adults age 60 and older with diabetes. *Telemedicine Journal & E-Health*, 12(6), 707-710.
- Braithwaite, D. O., Waldron, V. R., & Finn, J. (1999). Communication of social support in computer-mediated groups for people with disabilities. *Health communication*, 11(2), 123-151.
- Brandtzæg, P. B., & Heim, J. (2008). *User loyalty and online communities: why members of online communities are not faithful*. Paper presented at the Proceedings of the 2nd international conference on INtelligent TEchnologies for interactive enterTAINment.
- Brandtzæg, P. B., & Heim, J. (2007). Initial context, user and social requirements for the Citizen Media applications: Participation and motivations in off-and online communities. *Citizen Media Project*.
- Bretherton, I. (1985). Attachment theory: Retrospect and prospect. *Monographs of the society for research in child development*, 3-35.

- Bretherton, I. (1992). The origins of attachment theory: John Bowlby and Mary Ainsworth. *Developmental psychology*, 28(5), 759.
- Burke, M., Marlow, C., & Lento, T. (2009). *Feed me: motivating newcomer contribution in social network sites*. Paper presented at the Proceedings of the SIGCHI conference on human factors in computing systems.
- Butler, B. S. (2001). Membership size, communication activity, and sustainability: A resource-based model of online social structures. *Information Systems Research*, 12(4), 346-362.
- Butler, B. S., Bateman, P. J., Gray, P. H., & Diamant, E. I. (2014). An Attraction-Selection-Attrition Theory of Online Community Size and Resilience. *Mis Quarterly*, 38(3), 699-728.
- Cassidy, J., & Shaver, P. R. (2002). *Handbook of attachment: Theory, research, and clinical applications*: Rough Guides.
- Chou, W.-y. S., Liu, B., Post, S., & Hesse, B. (2011). Health-related Internet use among cancer survivors: data from the Health Information National Trends Survey, 2003–2008. *Journal of Cancer Survivorship*, 5(3), 263-270.
- Chuang, L.-W., Chiu, S.-P., He, J., & Chu, W.-C. (2015). *Exploring users' willingness to help the online community*. Paper presented at the Innovation in Design, Communication and Engineering: Proceedings of the 2014 3rd International Conference on Innovation, Communication and Engineering (ICICE 2014), Guiyang, Guizhou, PR China, October 17-22, 2014.
- Cline, R. J. W. (1999). Communication in social support groups. *The handbook of group communication theory and research*, 516-538.
- Cobb, S. (1976). Social support as a moderator of life stress. *Psychosomatic medicine*, 38(5), 300-314.
- Cohen, S. (2004). Social relationships and health. *American psychologist*, 59(8), 676.
- Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological bulletin*, 98(2), 310.
- Cohen, S. E., & Syme, S. (1985). *Social support and health*: Academic Press.
- Constant, D., Sproull, L., & Kiesler, S. (1996). The kindness of strangers: The usefulness of electronic weak ties for technical advice. *Organization Science*, 7(2), 119-135.
- Cotte, J., Chowdhury, T. G., Ratneshwar, S., & Ricci, L. M. (2006). Pleasure or utility? Time planning style and web usage behaviors. *Journal of Interactive Marketing*, 20(1), 45-57.
- Coursaris, C. K., & Liu, M. (2009). An analysis of social support exchanges in online HIV/AIDS self-help groups. *Computers in Human Behavior*, 25(4), 911-918.
- Courtney, K. (2013). The use of social media in healthcare: organizational, clinical, and patient perspectives. *Enabling Health and Healthcare Through ICT: Available, Tailored and Closer*, 183, 244.
- Crandall, D., Cosley, D., Huttenlocher, D., Kleinberg, J., & Suri, S. (2008). *Feedback effects between similarity and social influence in online communities*. Paper presented at the Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining.
- Cummings, J. N., Butler, B., & Kraut, R. (2002). The quality of online social relationships. *Communications of the ACM*, 45(7), 103-108.
- Cummins, R. C. (1988). Perceptions of social support, receipt of supportive behaviors, and locus of control as moderators of the effects of chronic stress. *American Journal of Community Psychology*, 16(5), 685-700.
- Cutrona, C. E. (1990). Stress and social support—In search of optimal matching. *Journal of social and clinical Psychology*, 9(1), 3-14.
- Cutrona, C. E., Shaffer, P. A., Wesner, K. A., & Gardner, K. A. (2007). Optimally matching support and perceived spousal sensitivity. *Journal of family psychology*, 21(4), 754.
- Cutrona, C. E., & Suhr, J. A. (1992). Controllability of stressful events and satisfaction with spouse support behaviors. *Communication Research*, 19(2), 154-174.
- Dabholkar, P. A., Shepherd, C. D., & Thorpe, D. I. (2000). A comprehensive framework for service quality: an investigation of critical conceptual and measurement issues through a longitudinal study. *Journal of retailing*, 76(2), 139-173.
- Dholakia, U. M., Bagozzi, R. P., & Pearo, L. K. (2004). A social influence model of consumer participation in network-and small-group-based virtual communities. *International journal of research in marketing*, 21(3), 241-263.
- Dick, A. S., & Basu, K. (1994). Customer loyalty: toward an integrated conceptual framework. *Journal of the academy of marketing science*, 22(2), 99-113.
- Diker, V. (2004). A Dynamic Feedback Framework for Studying Growth Policies in Open Online Collaboration Communities. *AMCIS 2004 Proceedings*, 2004, 328.
- Earnshaw, V. A., Lang, S. M., Lippitt, M., Jin, H., & Chaudoir, S. R. (2015). HIV stigma and physical health symptoms: do social support, adaptive coping, and/or identity centrality act as resilience resources? *AIDS and Behavior*, 19(1), 41-49.
- Faraj, S., & Johnson, S. L. (2011). Network exchange patterns in online communities. *Organization Science*, 22(6), 1464-1480.

- Fazio, R. H. (1995). Attitudes as object-evaluation associations: Determinants, consequences, and correlates of attitude accessibility. *Attitude strength: Antecedents and consequences*, 4, 247-282.
- Fogel, J., Albert, S. M., Schnabel, F., Ditkoff, B. A., & Neugut, A. I. (2002). Internet use and social support in women with breast cancer. *Health psychology*, 21(4), 398.
- Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research*, 19(3), 291-313.
- Franklin, V. L., Greene, A., Waller, A., Greene, S. A., & Pagliari, C. (2008). Patients' engagement with "Sweet Talk"—a text messaging support system for young people with diabetes. *Journal of Medical Internet Research*, 10(2).
- Frost, J. H., & Massagli, M. P. (2008). Social uses of personal health information within PatientsLikeMe, an online patient community: what can happen when patients have access to one another's data. *Journal of Medical Internet Research*, 10(3).
- Ghose, A. (2009). Internet exchanges for used goods: An empirical analysis of trade patterns and adverse selection. *Mis Quarterly*, 263-291.
- Greene, J. A., Choudhry, N. K., Kilabuk, E., & Shrank, W. H. (2011). Online social networking by patients with diabetes: a qualitative evaluation of communication with Facebook. *Journal of general internal medicine*, 26(3), 287-292.
- Gruen, T. W., Osmonbekov, T., & Czaplewski, A. J. (2006). eWOM: The impact of customer-to-customer online know-how exchange on customer value and loyalty. *Journal of Business research*, 59(4), 449-456.
- Guthrie, J. A., & Kunkel, A. (2016). Communication in Support Groups. *The International Encyclopedia of Interpersonal Communication*.
- Hackos, J. T., & Redish, J. (1998). *User and task analysis for interface design*. New York: Wiley Computer Publishing.
- Hall, H., & Graham, D. (2004). Creation and recreation: motivating collaboration to generate knowledge capital in online communities. *International Journal of Information Management*, 24(3), 235-246.
- Hallowell, R. (1996). The relationships of customer satisfaction, customer loyalty, and profitability: an empirical study. *International journal of service industry management*, 7(4), 27-42.
- Hansen, F., Smith, M., & Hansen, R. B. (2002). Rewards and recognition in employee motivation. *Compensation & Benefits Review*, 34(5), 64-72.
- Heaney, C. A., & Israel, B. A. (2008). Social networks and social support. *Health behavior and health education: Theory, research, and practice*, 4, 189-210.
- Helgeson, V. S., Cohen, S., Schulz, R., & Yasko, J. (2001). Long-term effects of educational and peer discussion group interventions on adjustment to breast cancer. *Health psychology*, 20(5), 387.
- Hesse, B. W., Moser, R. P., Rutten, L. J. F., & Kreps, G. L. (2006). The health information national trends survey: research from the baseline. *Journal of Health Communication*, 11(S1), vii-xvi.
- Himle, D. P., Jayaratne, S., & Thyness, P. (1991). *Buffering effects of four social support types on burnout among social workers*. Paper presented at the Social Work Research and Abstracts.
- Hong, S., & Kim, J. (2004). Architectural criteria for website evaluation—conceptual framework and empirical validation. *Behaviour & Information Technology*, 23(5), 337-357.
- Hossain, M. A., & Quaddus, M. (2012). Expectation–confirmation theory in information system research: A review and analysis *Information systems theory* (pp. 441-469): Springer.
- Hou, H. (2015). What makes an online community of practice work? A situated study of Chinese student teachers' perceptions of online professional learning. *Teaching and Teacher Education*, 46, 6-16.
- Høybye, M. T., Johansen, C., & Tjørnhøj - Thomsen, T. (2005). Online interaction. Effects of storytelling in an internet breast cancer support group. *Psycho - Oncology*, 14(3), 211-220.
- Hsu, M.-H., & Chiu, C.-M. (2004). Predicting electronic service continuance with a decomposed theory of planned behaviour. *Behaviour & Information Technology*, 23(5), 359-373.
- Huang, K.-Y., Chengalur-Smith, S., & Pinsonneault, A. (2014). Why Should I Provide Social Support? A Social Capital Perspective of Individual Helping Behavior in Healthcare Virtual Support Communities.
- Huh, J., McDonald, D. W., Hartzler, A., & Pratt, W. (2013). *Patient moderator interaction in online health communities*. Paper presented at the AMIA Annual Symposium Proceedings.
- Jabr, W., Mookerjee, R., Tan, Y., & Mookerjee, V. (2013). Leveraging philanthropic behavior for customer support: The case of user support forums.
- Jin, X.-L., Lee, M. K., & Cheung, C. M. (2010). Predicting continuance in online communities: model development and empirical test. *Behaviour & Information Technology*, 29(4), 383-394.
- Johnson, G. J., & Ambrose, P. J. (2006). Neo-tribes: the power and potential of online communities in health care. *Communications of the ACM*, 49(1), 107-113.

- Josefsson, U. (2005). Coping with illness online: the case of patients' online communities. *The Information Society*, 21(2), 133-141.
- Joyce, E., & Kraut, R. E. (2006). Predicting continued participation in newsgroups. *Journal of Computer - Mediated Communication*, 11(3), 723-747.
- Kang, I., Lee, K. C., Lee, S., & Choi, J. (2007). Investigation of online community voluntary behavior using cognitive map. *Computers in Human Behavior*, 23(1), 111-126.
- Kibria, C. G., Saha, B. N., & Howlader, U. J. (2016). Impact of Recognition on Motivation and Performance: The Case of SMEs In Dhaka City. *World*, 6(3), 100-112.
- Klemm, P., Bunnell, D., Cullen, M., Soneji, R., Gibbons, P., & Holecek, A. (2003). Online cancer support groups: a review of the research literature. *Computers Informatics Nursing*, 21(3), 136-142.
- Kraut, R. E., Resnick, P., Kiesler, S., Burke, M., Chen, Y., Kittur, N., . . . Riedl, J. (2012). *Building successful online communities: Evidence-based social design*: Mit Press.
- Kummervold, P. E., Gammon, D., Bergvik, S., Johnsen, J.-A. K., Hasvold, T., & Rosenvinge, J. H. (2002). Social support in a wired world: use of online mental health forums in Norway. *Nordic journal of psychiatry*, 56(1), 59-65.
- Lakhani, K. R., & Von Hippel, E. (2003). How open source software works: "free" user-to-user assistance. *Research policy*, 32(6), 923-943.
- Lampe, C., Wash, R., Velasquez, A., & Ozkaya, E. (2010). *Motivations to participate in online communities*. Paper presented at the Proceedings of the SIGCHI conference on Human factors in computing systems.
- Langford, C. P. H., Bowsher, J., Maloney, J. P., & Lillis, P. P. (1997). Social support: a conceptual analysis. *Journal of advanced nursing*, 25(1), 95-100.
- Lau, A. Y., & Kwok, T. M. (2009). Social features in online communities for healthcare consumers—a review *Online communities and social computing* (pp. 682-689): Springer.
- Laurent, G., & Kapferer, J.-N. (1985). Measuring consumer involvement profiles. *Journal of marketing research*, 22(1), 41-53.
- Lazar, J., & Preece, J. (2002). *Social considerations in online communities: Usability, sociability, and success factors*. Mahwah, NJ: Lawrence Erlbaum Associates Inc. Publishers.
- Ledbetter, A. M. (2009). Measuring online communication attitude: Instrument development and validation. *Communication Monographs*, 76(4), 463-486.
- Lee, M.-C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & Education*, 54(2), 506-516.
- Lee, M. K., Cheung, C. M., & Chen, Z. (2005). Acceptance of Internet-based learning medium: the role of extrinsic and intrinsic motivation. *Information & Management*, 42(8), 1095-1104.
- Lee, Y., Chen, A. N., & Ilie, V. (2012). Can Online Wait Be Managed? The Effect of Filler Interfaces and Presentation Modes on Perceived Waiting Time Online. *Mis Quarterly*, 36(2), 365-394.
- Lento, T., Welser, H. T., Gu, L., & Smith, M. (2006). *The ties that blog: Examining the relationship between social ties and continued participation in the wallop weblogging system*. Paper presented at the 3rd Annual Workshop on the Weblogging ecosystem.
- Lin, H.-F. (2007). The role of online and offline features in sustaining virtual communities: an empirical study. *Internet Research*, 17(2), 119-138.
- Ling, K., Beenen, G., Ludford, P., Wang, X., Chang, K., Li, X., . . . Rashid, A. M. (2005). Using social psychology to motivate contributions to online communities. *Journal of Computer - Mediated Communication*, 10(4), 00-00.
- Loane, S. S., Webster, C. M., & D'Alessandro, S. (2014). Identifying consumer value co-created through social support within online health communities. *Journal of Macromarketing*, 0276146714538055.
- Lu, Y., Zhang, P., Liu, J., Li, J., & Deng, S. (2013). Health-related hot topic detection in online communities using text clustering. *Plos one*, 8(2), e56221.
- Ma, M., & Agarwal, R. (2007). Through a glass darkly: Information technology design, identity verification, and knowledge contribution in online communities. *Information Systems Research*, 18(1), 42-67.
- Marco Leimeister, J., Schweizer, K., Leimeister, S., & Krcmar, H. (2008). Do virtual communities matter for the social support of patients? Antecedents and effects of virtual relationships in online communities. *Information Technology & People*, 21(4), 350-374.
- McCorkle, B. H., Rogers, E. S., Dunn, E. C., Lyass, A., & Wan, Y. M. (2008). Increasing social support for individuals with serious mental illness: Evaluating the compeer model of intentional friendship. *Community mental health journal*, 44(5), 359.
- McMillan, D. W., & Chavis, D. M. (1986). Sense of community: A definition and theory. *Journal of community psychology*, 14(1), 6-23.

- Meier, A., Lyons, E. J., Frydman, G., Forlenza, M., & Rimer, B. K. (2007). How cancer survivors provide support on cancer-related Internet mailing lists. *Journal of Medical Internet Research*, 9(2).
- Melmed, S., & Williams, R. H. (2011). *Williams textbook of endocrinology* (12th ed.). Philadelphia: Elsevier/Saunders.
- Meric, F., Bernstam, E. V., Mirza, N. Q., Hunt, K. K., Ames, F. C., Ross, M. I., . . . Singletary, S. E. (2002). Breast cancer on the world wide web: cross sectional survey of quality of information and popularity of websites. *Bmj*, 324(7337), 577-581.
- Millington, R. (2013). Almost Every Branded Community Fails – Some Case Studies. Retrieved from <https://www.feverbee.com/almost-every-branded-community-fails-some-case-studies/>
- Mowday, R. T., Steers, R. M., & Porter, L. W. (1979). The measurement of organizational commitment. *Journal of vocational behavior*, 14(2), 224-247.
- Nambisan, P. (2011). Information seeking and social support in online health communities: impact on patients' perceived empathy. *Journal of the American Medical Informatics Association*, 18(3), 298-304.
- Nath, C., Huh, J., Adupa, A. K., & Jonnalagadda, S. R. (2016). Website Sharing in Online Health Communities: A Descriptive Analysis. *Journal of Medical Internet Research*, 18(1), e11.
- Nonnecke, B., Preece, J., & Andrews, D. (2004). *What lurkers and posters think of each other [online community]*. Paper presented at the System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference on.
- Oliver, R. L., & Linda, G. (1981). Effect of satisfaction and its antecedents on consumer preference and intention. *ACR North American Advances*.
- Park, C. W., & Young, S. M. (1986). Consumer response to television commercials: The impact of involvement and background music on brand attitude formation. *Journal of marketing research*, 23(1), 11-24.
- Phang, C. W., Kankanhalli, A., & Sabherwal, R. (2009). Usability and sociability in online communities: A comparative study of knowledge seeking and contribution. *Journal of the Association for Information Systems*, 10(10), 2.
- Pietromonaco, P. R., Uchino, B., & Dunkel Schetter, C. (2013). Close relationship processes and health: implications of attachment theory for health and disease. *Health psychology*, 32(5), 499.
- Porter, L. W., Steers, R. M., Mowday, R. T., & Boulian, P. V. (1974). Organizational commitment, job satisfaction, and turnover among psychiatric technicians. *Journal of applied psychology*, 59(5), 603.
- Prentice, D. A., Miller, D. T., & Lightdale, J. R. (1994). Asymmetries in attachments to groups and to their members: Distinguishing between common-identity and common-bond groups. *Personality and Social Psychology Bulletin*, 20(5), 484-493.
- Ransbotham, S., & Kane, G. C. (2011). Membership turnover and collaboration success in online communities: Explaining rises and falls from grace in Wikipedia. *MIS Quarterly-Management Information Systems*, 35(3), 613.
- Ravert, R. D., Hancock, M. D., & Ingersoll, G. M. (2003). Online forum messages posted by adolescents with type 1 diabetes. *The Diabetes Educator*, 30(5), 827-834.
- Reid, F. J., Malinek, V., Stott, C. J., & Evans, J. S. B. (1996). The messaging threshold in computer-mediated communication. *Ergonomics*, 39(8), 1017-1037.
- Ren, Y., Kraut, R., & Kiesler, S. (2007). Applying common identity and bond theory to design of online communities. *Organization studies*, 28(3), 377-408.
- Ren, Y., & Kraut, R. E. (2011). A simulation for designing online community: Member motivation, contribution, and discussion moderation. *Information Systems Research*.
- Restivo, M., & Van De Rijdt, A. (2012). Experimental study of informal rewards in peer production. *Plos one*, 7(3), e34358.
- Reynolds, J. S., & Perrin, N. A. (2004). Mismatches in social support and psychosocial adjustment to breast cancer. *HEALTH PSYCHOLOGY-HILLSDALE*, 23(4), 425-429.
- Ridings, C. M., & Gefen, D. (2004). Virtual community attraction: Why people hang out online. *Journal of Computer - Mediated Communication*, 10(1), 00-00.
- Rodgers, S., & Chen, Q. (2005). Internet community group participation: Psychosocial benefits for women with breast cancer. *Journal of Computer - Mediated Communication*, 10(4), 00-00.
- Ryan, A. M., Sacco, J. M., McFarland, L. A., & Kriska, S. D. (2000). Applicant self-selection: Correlates of withdrawal from a multiple hurdle process. *Journal of applied psychology*, 85(2), 163.
- Sassenberg, K. (2002). Common bond and common identity groups on the Internet: Attachment and normative behavior in on-topic and off-topic chats. *Group Dynamics: Theory, Research, and Practice*, 6(1), 27.
- Savolainen, R. (2011). Requesting and providing information in blogs and internet discussion forums. *Journal of Documentation*, 67(5), 863-886.
- Shang, Y., & Liu, J. (2015). Users' Continuance Participation in the Online Peer-to-peer Healthcare Community: A Text Mining Approach.

- Shumaker, S. A., & Brownell, A. (1984). Toward a theory of social support: Closing conceptual gaps. *Journal of social issues*, 40(4), 11-36.
- Smithson, J., Sharkey, S., Hewis, E., Jones, R., Emmens, T., Ford, T., & Owens, C. (2011). Problem presentation and responses on an online forum for young people who self-harm. *Discourse Studies*, 13(4), 487-501.
- Stryker, S. (1987). *Identity theory: developments and extensions*. Oxford, England: John Wiley & Sons.
- Szolnoki, A., & Perc, M. (2010). Reward and cooperation in the spatial public goods game. *EPL (Europhysics Letters)*, 92(3), 38003.
- Tajfel, H., & Turner, J. C. (2004). *The Social Identity Theory of Intergroup Behavior*. New York, NY, US: Psychology Press.
- Tardini, S., & Cantoni, L. (2005). *A semiotic approach to online communities: Belonging, interest and identity in websites' and videogames' communities*. Paper presented at the Proceedings of the IADIS International Conference e-Society.
- Taylor, H. (2010). "Cyberchondriacs" on the Rise? Retrieved from <http://www.harrisinteractive.com/NewsRoom/HarrisPolls/tabid/447/ctl/ReadCustom%20Default/mid/1508/ArticleId/448/Default.aspx>
- Tedjamulia, S. J., Dean, D. L., Olsen, D. R., & Albrecht, C. C. (2005). *Motivating content contributions to online communities: Toward a more comprehensive theory*. Paper presented at the System Sciences, 2005. HICSS'05. Proceedings of the 38th Annual Hawaii International Conference on.
- Tops, M., Koole, S. L., IJzerman, H., & Buisman-Pijlman, F. T. (2014). Why social attachment and oxytocin protect against addiction and stress: Insights from the dynamics between ventral and dorsal corticostriatal systems. *Pharmacology Biochemistry and Behavior*, 119, 39-48.
- Tsai, H.-T., & Bagozzi, R. P. (2014). Contribution Behavior in Virtual Communities: Cognitive, Emotional, and Social Influences. *Mis Quarterly*, 38(1), 143-163.
- Turner, J. W., Grube, J. A., & Meyers, J. (2001). Developing an optimal match within online communities: An exploration of CMC support communities and traditional support. *Journal of Communication*, 51(2), 231-251.
- Turoff, M. (1991). Computer - mediated communication requirements for group support. *Journal of Organizational Computing and Electronic Commerce*, 1(1), 85-113.
- van der Eijk, M., Faber, M. J., Aarts, J. W., Kremer, J. A., Munneke, M., & Bloem, B. R. (2013). Using online health communities to deliver patient-centered care to people with chronic conditions. *Journal of Medical Internet Research*, 15(6), e115.
- Van der Heijden, H. (2004). User acceptance of hedonic information systems. *Mis Quarterly*, 28(4), 695-704.
- Velasquez, A., Wash, R., Lampe, C., & Bjornrud, T. (2014). Latent users in an online user-generated content community. *Computer Supported Cooperative Work (CSCW)*, 23(1), 21-50.
- Venkatesh, V., Speier, C., & Morris, M. G. (2002). User acceptance enablers in individual decision making about technology: Toward an integrated model. *Decision Sciences*, 33(2), 297-316.
- Vlahovic, T. A., Wang, Y.-C., Kraut, R. E., & Levine, J. M. (2014). *Support matching and satisfaction in an online breast cancer support community*. Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.
- Wang, X., Zhao, K., & Street, N. (2014). *Social support and user engagement in online health communities*. Paper presented at the International Conference on Smart Health.
- Wang, Y.-C., Kraut, R., & Levine, J. M. (2012). *To stay or leave?: the relationship of emotional and informational support to commitment in online health support groups*. Paper presented at the Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work.
- Wasko, M. M., & Faraj, S. (2000). "It is what one does": why people participate and help others in electronic communities of practice. *The Journal of Strategic Information Systems*, 9(2), 155-173.
- Waterson, P. (2006). Motivation in online communities. In S. Dasgupta (Ed.), *Encyclopedia of virtual communities and technologies* (pp. 334-337). Hershey, PA: Idea Group Reference.
- Williams, L. J., & Anderson, S. E. (1991). Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. *Journal of management*, 17(3), 601-617.
- Wolff, J. K., Schmiedek, F., Brose, A., & Lindenberger, U. (2013). Physical and emotional well-being and the balance of needed and received emotional support: Age differences in a daily diary study. *Social science & medicine*, 91, 67-75.
- Wright, K. B. (1999). Computer - mediated support groups: An examination of relationships among social support, perceived stress, and coping strategies. *Communication quarterly*, 47(4), 402-414.
- Wu, W.-Y., & Sukoco, B. M. (2010). Why should I share? Examining consumers' motives and trust on knowledge sharing. *Journal of Computer Information Systems*, 50(4), 11-19.
- Wykes, L. (1998). *Commitment in the Workplace: Theory, Research, and Application*, by John P. Meyer, Natalie J. Allen. *Human Resource Development Quarterly*, 9, 309-311.

- Xiong, L., & Liu, L. (2004). Peertrust: Supporting reputation-based trust for peer-to-peer electronic communities. *IEEE transactions on Knowledge and Data Engineering*, 16(7), 843-857.
- Yamin, C. K., Bitton, A., & Bates, D. W. (2010). E-cigarettes: a rapidly growing Internet phenomenon. *Annals of internal medicine*, 153(9), 607-609.
- Yan, L., & Tan, Y. (2014). Feeling blue? Go online: an empirical study of social support among patients. *Information Systems Research*, 25(4), 690-709.
- Young, C. (2013). Community management that works: how to build and sustain a thriving online health community. *Journal of Medical Internet Research*, 15(6), e119.
- Zacharia, G. (1999). *Collaborative reputation mechanisms for online communities*. Massachusetts Institute of Technology.
- Zhang, P. (2013). The affective response model: a theoretical framework of affective concepts and their relationships in the ICT context. *Mis Quarterly*, 37(1), 247-274.
- Zhao, J., Wang, T., & Fan, X. (2015). Patient value co-creation in online health communities: Social identity effects on customer knowledge contributions and membership continuance intentions in online health communities. *Journal of Service Management*, 26(1), 72-96.
- Zhao, K., Stylianou, A. C., & Zheng, Y. (2013). Predicting users' continuance intention in virtual communities: The dual intention-formation processes. *Decision support systems*, 55(4), 903-910.
- Zimet, G. D., Dahlem, N. W., Zimet, S. G., & Farley, G. K. (1988). The multidimensional scale of perceived social support. *Journal of personality assessment*, 52(1), 30-41.
- Zrebiec, J., & Jacobson, A. (2001). What attracts patients with diabetes to an internet support group? A 21 - month longitudinal website study. *Diabetic Medicine*, 18(2), 154-158.

APPENDIX

Logistic regression results (Study I)

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	79.3001	7	<.0001
Score	63.1035	7	<.0001
Wald	37.5484	7	<.0001

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	90.3	Somers' D	0.808
Percent Discordant	9.5	Gamma	0.809
Percent Tied	0.2	Tau-a	0.366
Pairs	4606	c	0.904

Regression results (Study II)

Model 1: Dependent variable: Short-term stage activeness

Analysis of Variance					
Source	DF	Sum of Squares	MeanSquare	F Value	Pr > F
Model	7	86227	12318	13.38	<.0001
Error	190	174918	920.62109		
Corrected Total	197	261145			

Root MSE	30.34174	R-Square	0.3302
Dependent Mean	16.47475	Adj R-Sq	0.3055
Coeff Var	184.17119		

Model 2: Dependent variable: Long-term stage activeness

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	1409621	201374	18.56	<.0001
Error	190	2061120	10848		
Corrected Total	197	3470741			

Root MSE	104.15374	R-Square	0.4061
Dependent Mean	50.17677	Adj R-Sq	0.3843
Coeff Var	207.57363		

